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Note to the Reader

The three chapters of this dissertation are self-contained research articles and can be read separately. They are preceded by an introduction that summarizes the research presented in this dissertation. The terms “paper” or “article” are used to refer to chapters. Chapter 2 is co-authored, which explains the use of the “we” pronoun

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Introduction

Financial markets have witnessed deep structural changes over the past two decades. Sustainable finance has been drawing increased attention from investors (institutional and retail), politicians, and companies. The first chapter of this thesis looks at the impact of socially responsible investors on firms' anti-social behavior. The second chapter investigates what motivates shareholders to push for firms' pro-social actions and evaluates the costs these decisions impose on firms. Simultaneously, regulatory frameworks governing trading venues in Europe have undergone significant evolution to ensure transparency, fairness, and stability in financial markets. The third part of this thesis evaluates how the limitation of less transparent trading venues has impacted market fragmentation and liquidity.

Should socially responsible investors screen out non-responsible firms from their portfolio, or should they rather invest in them and engage with management? The first chapter evaluates the effectiveness of these *exit* (divestment) and *voice* (engagement) strategies and uncovers the conditions under which each strategy is most impactful. The first contribution of the paper is to create a firm-level measure of exit and voice pressures for US firms from 2013 to 2020. I classify US mutual funds along the exit and voice dimensions, based on their portfolio holdings and their votes. I create the firm-level measures based on the percentage of equity owned by exit and voice funds. Then, I use exogenous variations in these exit and voice pressures to causally identify the effect of strategy on firms' pro-social efforts. My first result is that in general, only voice is effective. The second contribution of the paper is to uncover the conditions under which each strategy is most impactful. The effect of voice is stronger when board directors seek reelection and exit only works when the CEO owns many shares in their firm. The main takeaway of the paper is that executives and directors respond to their shareholders' demand for pro-sociality only when they have personal incentives to do so.

But what motivates shareholders to become pro-social activists? In the second chapter, written with Michele Fioretti and Simon C. Smith, we show that large individual investors (such as former CEOs or founders) push for visible, costly pro-social actions when their firm is

under media exposure. To show that, we exploit periods of Annual General Meetings: it's a period where firms' decisions have more publicity. The period of the AGM is the same every year, therefore it is exogenous from events that increase the demand for pro-sociality from society. For instance, we show that firms with an AGM and large individual shareholders are more likely to make donations at the beginning of covid, or are more likely to cut business ties with Russian companies right after the invasion of Ukraine. We interpret this result as reflecting the image concerns of these shareholders, as most of them are easily associated with a firm. Institutional shareholders tend to oppose these actions, as they do not have such image gains. We find that after a pro-social action, their Google Trends score increases by 50%, while that of institutional shareholders remains flat. Finally, we show that pursuing the value of these shareholders is costly to others: such decisions lower earnings by 1 to 3%.

The third chapter investigates whether we should regulate dark (non-pre-trade transparent) trading venues. This paper studies the impact of a European regulation (MiFID II's Double-Volume-Cap mechanism) limiting the use of dark trading venues on market fragmentation and liquidity. It says that if more than 8% of a stock's trading volume happened in dark pools over the past year, the stock cannot be traded in dark pools for the next 6 months. I show that dark volumes of banned stocks are redirected to lit venues and periodic auctions, in line with a "pecking order" of trading venues. Liquidity improves significantly on stock exchanges–compared to similar stocks unaffected by the ban–and the effect is concentrated among stocks with a high level of noise trading. Those results confirm the theoretical prediction that dark trading is detrimental to liquidity by increasing adverse selection risk on stock exchanges.

Chapter 1 | Exit or Voice? Divestment, Activism, and Corporate Social Responsibility

More than 5,000 institutional investors, representing $121 trillion in assets under management, have signed the UN's Principles for Responsible Investments.[1] But how can they pressure firms to behave more pro-socially? In his 2020 and 2021 letters to CEOs, Larry Fink invited board directors and managers to think about how the growing trend in responsible investing would affect their company's stock price. He warned that companies that do not embrace more sustainable business practices would face a higher cost of capital in the future. These statements summarize the threat of *exit*:[2] facing potential divestment from their shareholders,

[1] UN PRI's 2023 Annual Report.

[2] Following Hirschman (1970)'s terminology.

firms must act more pro-socially to keep their current stock price high and be able to raise funds at low cost in the future. On the other hand, Fink also claimed that BlackRock would vote against management and directors when they are not making sufficient progress on sustainability matters. This is one way activist investors use their *voice*: they push for change at firms in their portfolio by threatening to wield their voting power. Do firms respond to these exit and voice pressures? Under what conditions?

This paper investigates whether exit and voice strategies can promote pro-social efforts exploiting a novel channel of causation: the financial and career concerns of firm management. Exit shareholders threaten CEOs' compensation via their personal exposure to their firm's stock price, and activist shareholders threaten board directors' reelection through their votes. Executives and directors thus have *personal* incentives to respond to exit and voice pressures. This specific channel would provide an alternative to the cost of capital channel for exit (Berk and van Binsbergen, 2021), and could explain why some ESG-motivated activist campaigns are successful (e.g., Naaraayanan et al., 2021). Yet, an empirical evaluation of these mechanisms faces at least three challenges: *i)* measuring the exit and voice pressures faced by firms, *ii)* finding exogenous variations in these pressures, and *iii)* finding a proxy for firms' CSR efforts.

This paper makes two main contributions. The first contribution is to develop a novel classification of US mutual funds as exit, voice, both, or none. The quarterly classification covers almost 2,000 funds between 2013 and 2020. It allows me to build a firm-level measure of exit and voice pressures, based on the percentage of equity owned by exit and voice funds. Then, I use large redemptions from funds as plausibly exogenous shocks to exit and voice pressures to identify the impact of each strategy on listed US firms' CSR efforts, as proxied by the occurrence of media-reported social controversies.[3] The paper's second contribution is to assess the effectiveness of each strategy and to uncover the conditions under which they are most impactful.

I first identify *exit funds* using portfolio holdings data. I uncover funds' preference for pro-social stocks by applying the framework of Koijen and Yogo (2019). Namely, in each quarter, I regress the weight of each stock in a fund's portfolio on its financial characteristics and its Environmental, Social, and Governance scores. The coefficient on Social score (β_S) indicates whether, all else equal, a fund invests more in stocks with a higher level of CSR. This coefficient correlates with a name-based fund classification. In any given quarter, I define as

[3] I focus on the *social* dimension of firms' externalities as most of the ESG-related votes that reflect disagreement among shareholders and with the management fall into the "S" category. Moreover, funds that divest from firms with low environmental standards generally divest from whole industries (e.g., "Fossil Fuel Free" funds) rather than individual stocks. Finally, firms' pro-social efforts are more comparable across corporations and industries than their environmental efforts.

exit fund any non-index fund with a positive β_S.[4] The share of exit funds among non-index funds rose from 32% in 2013 to 45% in 2018. For every firm in every quarter, I build a measure of the *threat of exit* that the firm faces from its fund shareholders, as the share of its equity owned by exit funds.

I identify *voice funds* using their votes at the Annual General Meetings (AGMs) of firms in their portfolio. Gathering all funds' votes from the Securities and Exchange Commission's website, I focus on S-related shareholder-sponsored resolutions that are opposed by management. A fund's voice score in each quarter is the percentage of times its fund company voted in favor of these resolutions in the previous four quarters. I find that the propensity to vote in favor of CSR-related resolutions increases over my sample period and that most funds either vote always in favor or always against such proposals. To test the correlation of the voice score with alternative proxies, I show that participants in the Principles for Responsible Investment's "Advance" initiative, through which investors take action on social issues at firms in their portfolio, have a significantly higher voice score than others. I create a firm-level measure of voice pressure as the share of equity owned by funds with a voice score greater than 85% (i.e., above proxy advisors' percentage of favorable recommendation on the same set of resolutions).

Then, I develop a portable framework to identify funds' influence on firm policies. As a firm's shareholder composition is endogenous, I causally identify the impact of each strategy on CSR efforts by exploiting plausibly exogenous changes in funds' influence due to large fund redemptions. The idea is that when funds are forced to fire-sell some of their assets, they have less power to exert their threat of exit or their voice. For each firm in each quarter, I compute the hypothetical percentage of its equity sold by exit and voice funds due to large redemptions, as if funds liquidated their assets proportionally. I first use these shocks in an event study design. Then, in the spirit of shift-share instruments (Borusyak et al., 2022), I instrument the changes in firms' exposure to funds' exit and voice using these large redemptions and estimate their impact on the future behavior of firms.

I measure firms' CSR efforts based on social controversies published in the media. They are my preferred measure of CSR because they are observable at high frequency and allow the date of the underlying misbehavior to be identified. In addition, they reflect all dimensions of CSR, even those that are difficult to measure like corporate culture. Finally, they are publicly observable and thus trigger strong investor reactions in the form of negative abnormal returns and managerial turnover. It is precisely the fear of such punishments that may prompt the firm management to act in response to exit and voice pressures. Upon the occurrence of a controversy, exit funds — and not others — sell the stock, and managerial turnover is

[4]Index funds, by definition, cannot use the threat of exit.

concentrated among firms with high voice ownership.

My first result is that, in general, only voice is effective at promoting pro-social efforts. When voice funds are forced to sell 1% of a firm's equity, the probability that the firm faces a controversy increases by 10 to 20%. This result is consistent with the theoretical prediction of Broccardo et al. (2022), and is robust to multiple specifications and alternative classifications of exit and voice funds. The result is not driven by a change in media coverage: the number of non-ESG-related news is not impacted by changes in exit and voice pressures. Moreover, the result holds when using alternative measures of controversies such as NGO campaigns, or positive measures of CSR such as ESG scores, charitable donations, and board gender diversity.

I validate this result by exploiting a salient natural experiment where the motivation behind large fund redemptions can be identified. In 2018, the French investment bank Natixis reported more than USD 300 million in non-recurring losses due to derivative positions that bet on the rise of South Korea's main stock index. As the index fell from June to December 2018, Natixis cut its US equity fund holdings by almost 50%. I exploit the heterogeneity in funds' exposure to Natixis before the losses as a shock to funds' influence. Firms with high exposure to Natixis-owned voice funds saw a large decrease in voice pressure after the trading losses and a subsequent increase in controversies.

My second finding is that the unconditional null effect of exit hides some interesting heterogeneity. I find that firms with high CEO wealth-performance sensitivity (WPS) respond to the threat of exit. However, even among firms in the top quartile of the WPS distribution, the effect of exit is smaller in magnitude than the effect of voice. I do not find evidence that firms with a high cost of capital respond more to the threat of exit. On the contrary, the results, although weakly significant, tend to show that firms with a lower cost of capital are the most responsive.

My third result shows that firms respond more to voice pressure when board directors are seeking reelection. I derive this result by exploiting differences in board structures and exogenous variations in board renewal rates. The majority of US boards are entirely reelected every year, but some companies have board directors organized in "classes" with overlapping three-year terms. I find that this staggered board structure makes firms much less responsive to voice pressure. To (further) establish causality, I exploit year-on-year changes in board renewal rate arising from the fact that all classes of a board do not have the same size. The effect of voice on firms with staggered boards is concentrated in years when larger classes are reelected.

Finally, I illustrate the voice mechanism through firms' reactions to a successful activist campaign in their close vicinity. Specifically, I use the revolt led by activist funds against

Seaworld's board chairman as a shock to firms in the same industry and with shared voice ownership. This campaign was motivated by years of degraded reputation due to accusations of animal mistreatment and excessive executive compensation. In response, firms in Seaworld's network significantly improved their CSR behavior in the following quarters.

Overall, this paper develops and applies a portable framework to identify funds' preferences and their influence on firm policies. Taken together, my results indicate that executives and directors respond to their shareholders' demand for pro-sociality only when they have personal incentives to do so. This conclusion sheds light on a crucial mechanism leading firms to maximize shareholder welfare, rather than just profits (Hart and Zingales, 2017).

Chapter 2 | The Shared Cost of Pursuing Shareholder Value

Shareholder disagreements are common but often unobserved. As shareholders try to influence managers, policies have been implemented to inform shareholders (e.g., Desai et al., 2007) and resolve conflicts by allowing them to make proposals and vote at the Annual General Meetings (AGMs) of shareholders (e.g., DeMarzo, 1993, Bouton et al., 2022). However, some shareholders can also influence managers through private channels, reducing the ability of non-connected shareholders to access managers and limiting managerial knowledge regarding shareholder preferences over firms' decisions.

Social responsibility adds another dimension to shareholder conflicts because shareholders may disagree not only on the profitability of firms' actions, but also on their social implications (Landier et al., 2009, Fioretti, 2022). Consider Ford Motor's decision to convert some of its car production facilities to produce and donate medical ventilators to hospitals during the pandemic when ventilators, essential to treating patients with COVID-19, were in shortage. Due to its costs, shareholders might hold different views about the firm's decision. Those who derive "value" from covid relief may have supported it despite smaller financial returns as their cash donations could not help hospitals procure ventilators (Hart and Zingales, 2017). Shareholders easily associated with Ford Motor could benefit further from the media coverage of the firm's generosity, as is the case of Bill Ford, a member of the Ford family who, when interviewed by CBS, endorsed the donation of ventilators.[5] On the other hand, for shareholders such as US households who do not benefit from similar private returns, donations resemble

[5]"[...] When we look at this crisis– as a country and said, you know, which industry is positioned to help us not only in terms of sophisticated machinery, but can do a lotta them and a lotta them quickly, the auto industry is uniquely positioned to do that" (O'Donnell, 2020). This example is illustrative as ventilator productions were economically supported by the Defense Production Act (i.e., government contracts), while this paper focuses only on voluntary donations.

taxes (Friedman, 1970). These differences in preferences raise questions about the consequences of pursuing the values of some shareholders at the cost of others.

Our main contribution is to empirically investigate the shared costs of shareholders' influence by drawing a causal link between their preferences and the prosocial decisions of large global corporations. To overcome the main issue that we face, namely that shareholder influence is not observable, we focus on settings where a sudden emergency puts firms in an advantageous position to procure society with needed goods and services compared to what shareholders can achieve through cash donations. Exploiting the exogenous occurrence of AGMs as a shock to corporate news coverage, we find that the shareholders most likely to gain image returns from their firm's prosocial decisions demand positive changes. In contrast, shareholders with limited opportunities to extract private gains see these demands as externalities and oppose them because the associated costs can reduce a firm's profits and growth prospects. As a result, market capitalization and operating income drop by about one to three percentage points more at the firms most exposed to these externalities, resulting in adverse outcomes for "silent" and "unheard" shareholders. These losses come from inefficient expenses cutting current funds that would otherwise have been invested, describing a feedback loop curtailing future productivity.

Motivated by a stylized theoretical model of a contest where shareholders with different preferences about a corporate prosocial action compete to influence managers (e.g., Konrad et al., 2009), we expect that, net of prosocial inclinations, shareholders with significant shares in the firm and no private returns from its prosocial decision oppose the action if it reduces the firm's profits. On the contrary, shareholders who can gain private returns from the prosocial action will support it if these returns exceed their losses. Also inspired by the common ownership literature (e.g., Azar et al., 2018, Backus et al., 2021), we identify the former shareholders in institutional investors – financial intermediaries such as mutual funds and banks – whom the public hardly connects with a specific firm as they own shares across many firms, and the latter shareholders in individual and family shareholders, who are synonymous with a firm.[6] Importantly, some of these shareholders can be past or current managers without affecting our results, as discussed below.

Our empirical framework relies on a sudden emergency where the public demands firms to take costly prosocial actions and on the exogenous variation of AGM timing across firms, which we show to heighten a firm's media coverage, thereby increasing the media attention of its most recognizable shareholders. The International Shareholder Services (ISS), a global leader

[6]We present robustness checks using more sophisticated association measures between a firm and its shareholders, taking advantage of the Google search data for firms and shareholders.

in proxy voting services, requires firms to allow 90 days between the date when shareholders receive materials about the AGM proposals and the AGM. Consider the recent pandemic as a similar emergency. The first reported US covid case occurred on January 15, 2020 (Holshue et al., 2020): since the firms with AGMs planned for the following 90 days could not move their dates by law (SEA, 1934), the increased media attention due to the AGM period is independent of the preferences of shareholders and managers toward the donations, the composition of the shareholding body and their access to managers, and the financial and operational status of a firm. These features make our approach portable across crises (or even countries) and times.

Therefore, we estimate the impact of shareholder preferences on corporate decisions as the difference in the donation rates observed by April 15, 2020, across four groups of firms: *i)* the difference across treated firms (i.e., with an AGM before 90 days from the beginning of the crisis) with and without large individual (or institutional) shareholders and *ii)* the same difference across control firms (i.e., with no plans for an AGM in this period). Since firms donated covid-relief cash and goods like facemasks, sanitizing gels, and software, we focus on explaining why firms donated rather than the value of the donations. At S&P 500 firms, cash donations averaged 1% of EBIT alone, a substantial cost for a firm's shareholders but great publicity for the most visible ones.

We find that by April 15, treated S&P 500 firms are 9% more likely to donate to covid-relief if their shareholding body includes large individual shareholders before the pandemic compared to the average S&P 500 firm. In contrast, treated firms with large institutional shareholders are 15% less likely to donate compared to the average S&P 500 firm. Consumer demand for covid-related donations, managerial will, peer pressure from donating competitors, and financial returns do not explain our findings.

We validate the image-gain mechanism showing an instantaneous and sustained gap in the Google searches of the names of a firm's individual shareholders compared to those of its institutional shareholders around the donation news date; this gap widens by about 40% in each of the ten days following a donation. Nonetheless, institutional shareholders are not necessarily against covid-related donations: several S&P 500 financial firms donated directly, but their donations negatively correlate with those of the S&P 500 firms in their portfolios. Thus, shareholders support donations only if their influence yields direct private benefits, creating an externality on other shareholders. These returns can be micro-founded as warm glow utilities (e.g., Andreoni, 1989) or reputational gains from virtue signaling (e.g., Bar-Isaac et al., 2008).

We demonstrate the portability of our framework in two ways. First, we study another focal event of the last decade, namely the decision of US multinationals to forgo their Russian

investments or interrupt relationships with their Russian suppliers at the onset of the Ukrainian invasion in 2022. In this respect, we do not claim that exiting Russia was the welfare-enhancing choice, but rather that early exits could, on the one hand, receive greater media attention and, on the other, be particularly expensive for shareholders if they were not adequately planned. Our results regarding the directions of influence are consistent, with large institutional shareholders opposing exit decisions and individual shareholders supporting cutting ties with Russia. Second, we extend the scope of our influence mechanism by investigating firms' ESG news coverage and donations over the last decade. Consistent with our previous findings, large individual shareholding is associated with fewer prosocial incidents and more donations in the AGM month, validating our usage of AGMs for identification.

By providing goods unavailable in the markets, like sanitizing gels to hospitals or pressuring a villain state by terminating business dealings, firms had an advantage over shareholders in creating social value. As large individual shareholders benefited from these firms' responses, pursuing their values implied high costs for the others. Using operating income and market capitalization as measures of these costs, we find that these variables dropped at the most exposed firms by between one and three percentage points. In both cases, these drops are due to increased operating costs, as revenues stayed constant across treated and control firms. Indeed, in the covid case, we find that investment dropped by about 6% in 2020 and 2021 at the most exposed firms, leading to reduced productivity that compiled over time, costing shareholders about 3% of the average earnings-per-share (EPS) in the pre-period.[7] On the other hand, shareholders' influence on the Russian-Ukraine crisis led treated firms to rush out of Russia, with the most exposed firms reneging 20% more investments than control firms. As a result, unheard shareholders suffered: restructuring costs in 2022 eroded 5% of the EPS at the most exposed firms. In conclusion, pursuing the values of a few shareholders costs the others both today and in the future (e.g., Bartlett and Bubb, 2023, Edmans, 2023).

Chapter 3 | *Promise at Dawn:* Market Fragmentation and Liquidity when Dark Pools are Suspended

Recent technological and regulatory changes have revolutionized the way stocks are traded. While national stock exchanges used to act as quasi-monopolists, trading in a share now takes place on multiple venues at the same time. The development of alternative, self-regulated

[7]The EPS loss in 2020-21 is over 8% per standard deviation of a firm's share of individual shareholders among its shareholders with at least a 5% stake (ATE). Among the firms with large individual shareholders, an AGM at the onset of the pandemic decreased EPS by 21% (ATT), suggesting sizable costs for unheard shareholders.

trading venues has lead to lower fees and higher trading speed (Pagnotta and Philippon, 2018), but has also raised concerns about their impact on liquidity. Among them, dark pools have attracted a special attention from regulators and academics. By hiding their order book and offering potential price improvement, they are more likely to attract uninformed investors, increasing the share of informed traders on the reference lit exchange, which harms liquidity (Glosten and Milgrom, 1985, Zhu, 2014). However, estimating the impact of dark pools on stock exchanges' liquidity faces at least two challenges: 1) there is no guarantee that orders sent to the dark would have been sent to lit venues - and not other trading venue types - in a world without dark pools, and 2) there is an endogenous relationship between liquidity and venue selection.

Using the European regulation MiFID II as a quasi-natural experiment, this paper studies the effect of banning dark pools on market fragmentation and liquidity. Implemented in 2018, MiFID II introduces a cap on the use of dark pools in the European Union. Over a rolling twelve-month period, trading of any stock across dark pools is limited to 8% of its volume. A breach of this threshold means that dark trading for that security is suspended for six months. More than 700 stocks were subject to that suspension on March 12, 2018, and the impact has been significant: European dark pools lost one-third of their market-share, almost overnight. I develop a simple model based on Zhu (2014) that predicts that such regulation should significantly improve liquidity on stock exchanges.

First, I estimate that between a third and a half of the dark volumes are redirected to reference lit exchanges when access to dark pools is suspended. The remaining dark volumes are mostly redirected to periodic auctions, while the impact on Systematic Internalisers, Over-the-Counter trading and alternative lit venues is insignificant. Assuming that traders sort various trading venue types according to their cost and immediacy, a "pecking order" analysis (Menkveld et al., 2017) reveals that dark pools are in between lit venues and auctions. They attract relatively more patient traders than the former, and relatively more impatient traders than the latter. Banning dark venues introduces a direct trade-off between lit venues and auctions, explaining why those are the two venue types gaining market share after the ban.

Second, using the regulation to overcome the endogenous relationship between liquidity and venue selection, this paper identifies the causal effect of the ban on liquidity. To ensure comparability between treated and control stocks, I first implement a propensity score matching procedure, based on pre-treatment baseline covariates, and run a two-way fixed effect regression on the matched sample. Then, I implement a Synthetic Difference-in-Differences approach (Arkhangelsky et al., 2021), with unit and time weights, based on pre-treatment liquidity measures. My results show that suspending stocks from trading in the dark narrows

their spread by 10% and the price impact by 5%.

Finally, I document that the effect is concentrated among stocks with a high level of retail ownership, a common proxy for noise trading (Foucault et al., 2011, Peress and Schmidt, 2019). A higher level of retail ownership is associated with a larger decrease in spread and price impact, but it is not associated with a stronger increase in the market share of the reference lit exchange. This last result confirms that it is the degree informativeness of orders, and not just trading volumes, that causes the liquidity improvement.

Taken together, those results are in line with the theoretical prediction that dark pools attract uninformed orders that would otherwise be sent to lit venues (Zhu, 2014). They tend to confirm that dark pools are detrimental to market quality by increasing adverse selection risk on stock exchanges. To summarise, banning dark pools redirects (some) trading volumes to reference lit exchanges, decreasing the share of informed trading and improving liquidity.

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Chapter 1

Exit or Voice? Divestment, Activism, and Corporate Social Responsibility*

Abstract

Should ESG-motivated investors screen out non-responsible firms from their portfolio, or should they rather invest in them and engage with the management? This paper evaluates the effectiveness of these exit and voice strategies and uncovers the conditions under which each strategy is most impactful. Using a novel classification framework based on US mutual funds' portfolio holdings and votes on shareholder proposals, I show that voice funds are generally more effective than exit funds at pushing firms towards more socially responsible behavior. The exit strategy relies on the threat of lower stock prices and is effective only in firms with high CEO wealth-performance sensitivity. Voice funds threaten directors' reelection and are more effective when elections are approaching. Taken together, my results point to the financial and career concerns of the top management as driving pro-social change when shareholders demand it.

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1.1 Introduction

More than 5,000 institutional investors, representing $121 trillion in assets under management, have signed the UN's Principles for Responsible Investments.[1] But how can they pressure firms to behave more pro-socially? In his 2020 and 2021 letters to CEOs, Larry Fink invited board directors and managers to think about how the growing trend in responsible investing would affect their company's stock price. He warned that companies that do not embrace more sustainable business practices would face a higher cost of capital in the future. These statements summarize the threat of *exit*:[2] facing potential divestment from their shareholders, firms must act more pro-socially to keep their current stock price high and be able to raise funds at low cost in the future. On the other hand, Fink also claimed that BlackRock would vote against management and directors when they are not making sufficient progress on sustainability matters. This is one way activist investors use their *voice*: they push for change at firms in their portfolio by threatening to wield their voting power. Do firms respond to these exit and voice pressures? Under what conditions?

This paper investigates whether exit and voice strategies can promote pro-social efforts exploiting a novel channel of causation: the financial and career concerns of firm management. Exit shareholders threaten CEOs' compensation via their personal exposure to their firm's stock price, and activist shareholders threaten board directors' reelection through their votes. Executives and directors thus have *personal* incentives to respond to exit and voice pressures. This specific channel would provide an alternative to the cost of capital channel for exit (Berk and van Binsbergen, 2021), and could explain why some ESG-motivated activist campaigns are successful (e.g., Naaraayanan et al., 2021). Yet, an empirical evaluation of these mechanisms faces at least three challenges: *i)* measuring the exit and voice pressures faced by firms, *ii)* finding exogenous variations in these pressures, and *iii)* finding a proxy for firms' CSR efforts.

This paper makes two main contributions. The first contribution is to develop a novel classification of US mutual funds as exit, voice, both, or none. The quarterly classification covers almost 2,000 funds between 2013 and 2020. It allows me to build a firm-level measure of exit and voice pressures, based on the percentage of equity owned by exit and voice funds. Then, I use large redemptions from funds as plausibly exogenous shocks to exit and voice pressures to identify the impact of each strategy on listed US firms' CSR efforts, as proxied by the occurrence of media-reported social controversies.[3] The paper's second contribution is to

[1] UN PRI's 2023 Annual Report.

[2] Following Hirschman (1970)'s terminology.

[3] I focus on the *social* dimension of firms' externalities as most of the ESG-related votes that reflect disagreement among shareholders and with the management fall into the "S" category. Moreover, funds that divest from firms

assess the effectiveness of each strategy and to uncover the conditions under which they are most impactful.

I first identify *exit funds* using portfolio holdings data. I uncover funds' preference for pro-social stocks by applying the framework of Koijen and Yogo (2019). Namely, in each quarter, I regress the weight of each stock in a fund's portfolio on its financial characteristics and its Environmental, Social, and Governance scores. The coefficient on Social score (β_S) indicates whether, all else equal, a fund invests more in stocks with a higher level of CSR. This coefficient correlates with a name-based fund classification. In any given quarter, I define as exit fund any non-index fund with a positive β_S.[4] The share of exit funds among non-index funds rose from 32% in 2013 to 45% in 2018. For every firm in every quarter, I build a measure of the *threat of exit* that the firm faces from its fund shareholders, as the share of its equity owned by exit funds.

I identify *voice funds* using their votes at the Annual General Meetings (AGMs) of firms in their portfolio. Gathering all funds' votes from the Securities and Exchange Commission's website, I focus on S-related shareholder-sponsored resolutions that are opposed by management. A fund's voice score in each quarter is the percentage of times its fund company voted in favor of these resolutions in the previous four quarters. I find that the propensity to vote in favor of CSR-related resolutions increases over my sample period and that most funds either vote always in favor or always against such proposals. To test the correlation of the voice score with alternative proxies, I show that participants in the Principles for Responsible Investment's "Advance" initiative, through which investors take action on social issues at firms in their portfolio, have a significantly higher voice score than others. I create a firm-level measure of voice pressure as the share of equity owned by funds with a voice score greater than 85% (i.e., above proxy advisors' percentage of favorable recommendation on the same set of resolutions).

Then, I develop a portable framework to identify funds' influence on firm policies. As a firm's shareholder composition is endogenous, I causally identify the impact of each strategy on CSR efforts by exploiting plausibly exogenous changes in funds' influence due to large fund redemptions. The idea is that when funds are forced to fire-sell some of their assets, they have less power to exert their threat of exit or their voice. For each firm in each quarter, I compute the hypothetical percentage of its equity sold by exit and voice funds due to large redemptions, as if funds liquidated their assets proportionally. I first use these shocks in an event study design. Then, in the spirit of shift-share instruments (Borusyak et al., 2022), I instrument the

with low environmental standards generally divest from whole industries (e.g., "Fossil Fuel Free" funds) rather than individual stocks. Finally, firms' pro-social efforts are more comparable across corporations and industries than their environmental efforts.

[4]Index funds, by definition, cannot use the threat of exit.

changes in firms' exposure to funds' exit and voice using these large redemptions and estimate their impact on the future behavior of firms.

I measure firms' CSR efforts based on social controversies published in the media. They are my preferred measure of CSR because they are observable at high frequency and allow the date of the underlying misbehavior to be identified. In addition, they reflect all dimensions of CSR, even those that are difficult to measure like corporate culture. Finally, they are publicly observable and thus trigger strong investor reactions in the form of negative abnormal returns and managerial turnover. It is precisely the fear of such punishments that may prompt the firm management to act in response to exit and voice pressures. Upon the occurrence of a controversy, exit funds — and not others — sell the stock, and managerial turnover is concentrated among firms with high voice ownership.

My first result is that, in general, only voice is effective at promoting pro-social efforts. When voice funds are forced to sell 1% of a firm's equity, the probability that the firm faces a controversy increases by 10 to 20%. This result is consistent with the theoretical prediction of Broccardo et al. (2022), and is robust to multiple specifications and alternative classifications of exit and voice funds. The result is not driven by a change in media coverage: the number of non-ESG-related news is not impacted by changes in exit and voice pressures. Moreover, the result holds when using alternative measures of controversies such as NGO campaigns, or positive measures of CSR such as ESG scores, charitable donations, and board gender diversity.

I validate this result by exploiting a salient natural experiment where the motivation behind large fund redemptions can be identified. In 2018, the French investment bank Natixis reported more than USD 300 million in non-recurring losses due to derivative positions that bet on the rise of South Korea's main stock index. As the index fell from June to December 2018, Natixis cut its US equity fund holdings by almost 50%. I exploit the heterogeneity in funds' exposure to Natixis before the losses as a shock to funds' influence. Firms with high exposure to Natixis-owned voice funds saw a large decrease in voice pressure after the trading losses and a subsequent increase in controversies.

My second finding is that the unconditional null effect of exit hides some interesting heterogeneity. I find that firms with high CEO wealth-performance sensitivity (WPS) respond to the threat of exit. However, even among firms in the top quartile of the WPS distribution, the effect of exit is smaller in magnitude than the effect of voice. I do not find evidence that firms with a high cost of capital respond more to the threat of exit. On the contrary, the results, although weakly significant, tend to show that firms with a lower cost of capital are the most responsive.

My third result shows that firms respond more to voice pressure when board directors

are seeking reelection. I derive this result by exploiting differences in board structures and exogenous variations in board renewal rates. The majority of US boards are entirely reelected every year, but some companies have board directors organized in "classes" with overlapping three-year terms. I find that this staggered board structure makes firms much less responsive to voice pressure. To (further) establish causality, I exploit year-on-year changes in board renewal rate arising from the fact that all classes of a board do not have the same size. The effect of voice on firms with staggered boards is concentrated in years when larger classes are reelected.

Finally, I illustrate the voice mechanism through firms' reactions to a successful activist campaign in their close vicinity. Specifically, I use the revolt led by activist funds against Seaworld's board chairman as a shock to firms in the same industry and with shared voice ownership. This campaign was motivated by years of degraded reputation due to accusations of animal mistreatment and excessive executive compensation. In response, firms in Seaworld's network significantly improved their CSR behavior in the following quarters.

Overall, this paper develops and applies a portable framework to identify funds' preferences and their influence on firm policies. Taken together, my results indicate that executives and directors respond to their shareholders' demand for pro-sociality only when they have personal incentives to do so. This conclusion sheds light on a crucial mechanism leading firms to maximize shareholder welfare, rather than just profits (Hart and Zingales, 2017).

Literature. This paper falls into the literature studying the influence of shareholders on firms' CSR decisions (Gillan and Starks, 2003, Aggarwal et al., 2011). Abstracting from investors' motivations to adopt a pro-social investment mandate,[5] I contribute to the literature on the optimal shareholders' strategy to promote social responsibility among firms in their portfolios by studying exit and voice within a single framework. Studying this question in a CSR setting departs from the traditional corporate governance literature on several dimensions. Models of the threat of exit like Admati and Pfleiderer (2009) show that a blockholder's threat of exit has two components: the immediate price impact of a trade, and a signaling component, as other investors observe and learn about the fundamental value of the firm from the blockholder's decision. In a CSR setting, one could expect the threat of exit to be less effective, as CSR-indifferent (or even CSR-adverse) investors can buy back the shares sold by ESG funds

[5]Potential explanations include image concerns and reputation (Mésonnier and Nguyen, 2020, Fioretti et al., 2023), value alignment (Pástor et al., 2021, Pedersen et al., 2021, Bonnefon et al., 2022), the concern of having a positive social impact (Barber et al., 2021, Green and Roth, 2021), increasing firm value (Cuñat et al., 2012, Gollier and Pouget, 2014), a mix of social and financial returns (Dyck et al., 2019), and past experience of social irresponsibility (von Beschwitz et al., 2022).

due to anti-social behavior. It is also unclear what could motivate shareholders to bear the cost of pro-social activism, where traditional models assume that intervention increases firm value (e.g., Edmans and Manso, 2011).[6] In Broccardo et al. (2022), activists' gains come from their altruism: it is an empirical question of whether this altruism is strong enough for shareholders to put significant effort into their engagement. However, as the cost of a pro-social policy is shared among shareholders, they show that a majority of slightly altruistic investors is enough for voice to be more effective than exit.

This paper sheds light on the mechanisms through which exit and voice investors affect firms' CSR efforts. Previous papers have shown that the optimal strategy may depend on stock liquidity (Edmans et al., 2013) but also on other shareholders, for both strategic complementary and free-riding incentives (Edmans and Manso, 2011, Appel et al., 2019, Brav et al., 2021). The mechanism for voice could explain successful ESG-motivated activist campaigns (Akey and Appel, 2019, Chu and Zhao, 2019, Naaraayanan et al., 2021) which resonates with the literature on career concerns (Dewatripont et al., 1999, Gantchev and Giannetti, 2021, Fos and Tsoutsoura, 2014, Aggarwal et al., 2019). It provides an alternative explanation than the one based on firms' reputation (Dimson et al., 2015). Previous mechanisms of the threat of exit include firms' cost of equity (Berk and van Binsbergen, 2021), liquidity (Edmans et al., 2013), and executive compensation (Edmans, 2009, Admati and Pfleiderer, 2009, Bharath et al., 2013, Gantchev et al., 2022).

The fund classification developed in this paper builds on several contributions. The methodology used to identify exit funds relies on the empirical specification adopted by Koijen and Yogo (2019) in their "demand system approach" to asset pricing (see also Koijen et al., 2023). I augment their setting by including ESG scores as additional characteristics affecting funds' portfolio allocation decisions (an idea also implemented in other papers, e.g., Gibson et al., 2020, Noh et al., 2022).[7] The measure of exit is based both on current and past holdings, to capture both "tilting" and complete divestment strategies, although the former is expected to be more effective (Edmans et al., 2022).

To measure shareholder activism, Gillan and Starks (2000) advocate for using mutual fund votes, which are publicly available. My fund-level measure of voice confirms the previous results that most funds do not "blindly" follow proxy advisors' recommendations (Iliev and Lowry, 2015), and tend to be less pro-social than them (Bolton et al., 2020).

[6] Lewellen and Lewellen (2022) quantify those gains in the case of mutual funds.

[7] I refrain from using mutual funds' names to identify exit funds, as mutual fund misclassification is not unheard of (Chen et al., 2021). BNY Mellon have for instance been charged by the SEC for misstatement regarding the ESG considerations of their funds. Appendix 1.B explores the relationship between the main measure of exit and a name-based fund classification.

Finally, the identification strategy in this paper relies on mutual fund redemptions, in the light of the seminal papers by Coval and Stafford (2007) and Edmans et al. (2012). A large empirical literature has used fire sales to study the impact of stock underpricing or noise trading on corporate decisions such as equity issuances, R&D expenditures or investment (Khan et al., 2012, Hau and Lai, 2013, Phillips and Zhdanov, 2013, Acharya et al., 2014, Dessaint et al., 2019) but also on shareholder activism (Derrien et al., 2013, Norli et al., 2015).[8] The mutual fund redemptions are used as a "shift" in a shift-share instrument setting (Adao et al., 2019, Goldsmith-Pinkham et al., 2020, Borusyak et al., 2022). Closest to my paper in terms of methodology, Heath et al. (2023) use large inflows to SRI funds to identify their impact on CSR, and Green and Vallee (2022) study lending bans to the coal industry in a shift-share instrument setting.

Outline. This paper proceeds as follows. Section 1.2 develops the classification of US mutual funds along the exit and voice dimensions. Section 1.3 describes the identification strategy based on large redemptions. Section 1.4 evaluates the impact of exit and voice on firms' CSR efforts. Section 1.5 validates the results by exploiting a natural experiment where the motivation behind fund redemptions is known. Section 1.6 explores the conditions under which each strategy is most impactful. Section 1.7 concludes.

1.2 Sample Selection, Variables, and Summary Statistics

Starting from the whole universe of listed firms and US mutual funds, this section describes the sample selection procedure, data sources, and the measures of exit and voice at the fund and firm level.

1.2.1 Data and Sample Selection

Firms. Data on stock prices, firm characteristics, and ESG scores are from Refinitiv and retrieved at the quarterly frequency. I start from the entire universe of US-listed and US-headquartered firms in Refinitiv from 2010 to 2020 and exclude all firms with missing stock prices or number of shares. From that sample of 2,599 firms, I select those with at least 1% of

[8]Recent studies have questioned the relevance of these shocks to study non-fundamental variations in stock prices, as they are correlated with contemporaneous returns (Wardlaw, 2020), and lead to selection in the fire sales (Berger, 2021). I believe that they are not a threat to my main results as I do not use price or return variables as outcome variables or in the instrument, and I show the robustness of my main result on voice when using only pure index funds, for which there should be no selection bias in the fire sales. I also show that selection bias in the fire sales is unlikely to drive the main result for exit in Appendix 1.B.

mutual fund ownership in all quarters, and an average of at least 10% over the period. The final sample comprises 1,910 firms. As reported in Table 1.1, the average market capitalization in the sample is around USD 10 billion (hence these firms in the sample account for the vast majority of the US stock market capitalization). Yearly accounting data, as well as information on board structure, and CEO compensation, are from Refinitiv. From Audit Analytics I recover the dates of directors' terms as well as the reason for ending their term. CEO wealth-performance sensitivity data comes from Alex Edmans' website (Edmans et al., 2009).

Controversies. A firm's social externalities are inherently hard to measure (Fioretti, 2022). My main measure of a firm's CSR efforts is a dummy indicating the occurrence of a social controversy in the media, constructed using Ravenpack's news data. That measure is supposed to capture both firms' observable and unobservable CSR efforts and covers all dimensions of CSR. Starting from the entire universe of news about a firm, I select S-related news reporting a recent misbehavior. Examples of such news include racial and gender discrimination, accusations or legal pursuit for fraud, anti-competitive practices, or employee mistreatment. Distinguishing between the date of the article and the date of the controversial behavior is crucial: for instance, a 2013 article reporting that Abercrombie & Fitch was found guilty of discrimination when they fired an employee wearing a hijab in 2011 does not reflect Abercrombie's CSR efforts in 2013.[9] To that end, I follow Ravenpack's guidelines (Ravenpack, 2022) to identify controversies about an event that is less than 90 days old. That leaves a sample of more than 11,000 controversies reflecting recent misbehavior (406 firms in the sample are concerned). As the probability of facing a controversy in a given quarter for a firm is low (2.5%), I focus on the occurrence of controversies, rather than their count. Three examples of social controversies can be found in Figure 1.1, regarding Costco, Starbucks, and Google on topics related to human rights, racial discrimination, and unethical lobbying.

There are several advantages to using public controversies as the main dependent variable. First, they are publicly observed, easy to measure, and available at a high frequency. For these reasons, they matter to investors and managers of the firms. Using controversies allows me to closely link a change in the pro-social reputation of a firm and the personal incentives of executives and directors. I find that a firm facing a public controversy suffers from a 1% *negative* abnormal returns over the following 10 days (Figure 1.2), and it increases the probability of a director or officer resignation by almost 50% over the following two quarters (bottom panel of Figure 1.2).[10] Second, controversies are harder to manipulate than ESG scores as they do not

[9] `https://www.eeoc.gov/newsroom/abercrombie-fitch-liable-religious-discrimination-eeoc-suit-court-says`.

[10] Neither creditors nor consumers seem to react, as measured by the average interest rate (Figure 1.A2) or sales

rely on self-disclosed data, and also reflect dimensions of CSR that are harder to measure, such as corporate culture (Guiso et al., 2015).[11]

Other CSR measures. As an alternative measure of controversy, I use data on NGO campaigns. The dataset comes from Sigwatch (Koenig, 2017, Hatte and Koenig, 2020), a European consultancy tracking and analyzing NGO campaigns around the world. A campaign is defined as an event launched by an NGO against one or several companies on a given topic. The available dataset indicates the date on which a campaign has been made public in a report on an NGO's website, the company(ies) targeted, the topic of the campaign ("GMOs in food" for instance), a measure of the sentiment of the campaign toward the firm(s) from the most negative tone (-2) to the most positive (+2), and the prominence of the firm in the report (whether the firm is mentioned in the headline of the report, elsewhere in the communication, etc). I keep S-related campaigns targeting only one firm listed and headquartered in the US, with the most negative tone ($sentiment = -2$) and in which the firm is mentioned in the headline ($prominence = 4$). I also gather alternative, "positive" measures of CSR from Refinitiv: firms' E, S, and G scores, donations to revenue, and percentage of females sitting on the board. As a measure of board gender diversity, I use that percentage as well as a dummy indicating the absence of female directors (which is the case for 13% of the observations in the sample).[12]

Funds. Data on US mutual funds and their portfolio holdings come from the *Center for Research in Security Prices* (CRSP), at the quarterly frequency. I exclude all funds specialized in one sector (using their Lipper objective code) as large redemptions from these funds could plausibly be related to controversies in a group of firms (for instance, in the textile industry). I keep funds with at least 80% of their Total Net Assets (TNA) invested in US stocks, and that have at least 20 strictly positive holdings. The final sample of 1,995 US mutual funds owns on average 20% of the firms in the sample (Table 1.1), and their ownership typically ranges from 10% to 33% of firms' equity. Table 1.2 reports summary statistics on the funds. Funds in the sample manage on average USD 2.5 billion of US stocks, driven by large funds as the median is only USD 440 million. They hold on average 147 stocks (the median is only 64) and

over total assets (Figure 1.A3): only shareholders (and ESG data providers, Figure 1.A4) "punish" controversies.

[11] A recent literature investigates how firms manipulate their scoring: Akey et al. (2021) show that firms increase their charitable donations following data breach controversies to rebuild their reputation and increase their Social score, and Duchin et al. (2022) show that after an environmental controversy, firms sell their polluting plants to other firms in their supply chain, and increase their Environmental score without decreasing overall pollution.

[12] One could expect the threat of exit to be less effective to motivate positive changes, rather than discouraging bad actions (Admati and Pfleiderer, 2009).

have an investment universe (the number of unique stocks currently held or held in the past 11 quarters) of 255 stocks.

1.2.2 Measuring Exit

An exit fund is defined as a fund that, all else equal, invests more in companies with high social standards. A company with divestors as shareholders might be incentivized to have a more socially responsible behavior, as any decrease in ESG score or any controversy may lead to large share sales from them.

Exit classification at the fund level. The classification relies on demand function estimation, extending the approach of Koijen and Yogo (2019) and Koijen et al. (2023) to account for ESG considerations. Funds decide their portfolio allocation in a quarter taking as given stocks' characteristics: Log Market Equity, Log Book Equity, Profitability, Investment, Dividends-to-Book Equity, and Market Beta. The investable universe comprises 2,950 North American firms with non-missing stock price and number of shares, regardless of their mutual fund ownership. The choice of characteristics is motivated by the Five-Factor model of Fama and French (2015) and their construction follows Koijen and Yogo (2019). Any stock with missing baseline characteristics in a given quarter or not listed in the US is considered an "outside asset". I include stocks' Environmental, Social, and Governance scores (ranging from 0 to 100) as additional characteristics. Refinitiv's ESG scores are based on companies' filings and Annual Reports, which give a slowly changing measure of a firm's CSR, as they are typically reviewed once a year. For stocks with missing ESG scores, I attribute them a 0 because of information asymmetry, in the spirit of Noh et al. (2022). While ESG scores have recently been criticized for being extremely noisy (Berg et al., 2022), what matters here is not that they correctly measure a firm's pro-sociality, but rather that they are actually used by investors in their portfolio allocation decision. I define the investment universe for each investor as the set of stocks currently held or ever held in the previous 11 quarters. For each fund in each quarter, I construct an instrument for the market capitalization of each stock based on the investment universe and the AUM of other investors. For each investor and each quarter, I estimate the following characteristic-based demand function, using all stocks in the investment universe (including stocks that are not currently held):

$$\frac{w_{i,t}(n)}{w_{i,t}(0)} = \exp\{\alpha_{i,t} + \beta_{1,i,t} \times \hat{\mathrm{m}}_{i,t}(n) + \beta'_{2,i,t} \times \mathrm{x}_t(n) + \beta_{S,i,t} \times \text{ Social score}_t(n)\}\epsilon_{i,t}(n), \tag{1.1}$$

where $w_{i,t}(n)$ is the weight of asset n in fund i portfolio at time t, and $w_{i,t}(0)$ is the weight of the outside asset, $\hat{m}_{i,t}(n)$ is the instrument for asset n's market capitalization for investor i at time t, and $x_t(n)$ are the other characteristics of the stock (Log Book Equity, Profitability, Investment, Dividends-to-Book Equity, Market Beta, Environmental Score, and Governance Score). $\beta_{S,i,t}$ is the elasticity of demand to the Social score.

For investors with more than 750 strictly positive holdings in the cross-section, Equation 1.1 can be estimated directly. For investors with less than 750 holdings, I estimate their demand function using a ridge regression, with the (equal-weighted) average of large investors' coefficients as target coefficients, and a penalty of $\frac{120}{N_{i,t}^{0.7}}$, where $N_{i,t}$ is the number of stocks in the investment universe of fund i in quarter t. In any case, I make sure that $\beta_{1,i,t}$ is strictly less than 1, in line with the empirical evidence that demand functions are downward sloping (Shleifer, 1986, Kaul et al., 2000, Schultz, 2008, Gabaix and Koijen, 2021).[13] As this estimation also includes zero holdings, it takes into account stocks from which the fund exited in the past 11 quarters.

The coefficient $\beta_{S,i,t}$ is of particular interest for this study. It is interpreted as the change in demand of a specific fund in a given quarter when the Social score of a firm changes by 1, and it shows, all else equal, whether a fund invests more in firms with higher Social scores. The distribution of the coefficient is plotted in the top panel of Figure 1.3, and is relatively stable over time: the coefficient of correlation between $\beta_{S,i,t}$ and $\beta_{S,i,t-1}$ is 73% (p-value $< 1\%$). I then define as an exit fund in quarter t any non-index fund with:

$$\beta_{S,i,t} > 0.$$

Relevance of the exit measure. Does the exit score actually capture divestment? I test whether funds with higher exit scores are more likely to reduce their investment in a stock facing a controversy with an event study of the share of equity owned by exit and non-exit funds around the publication of the controversy. To avoid endogeneity between the exit classification and the controversy, for every controversy faced by a firm n at time t, I fix the exit classification at $t-1$. Then, the ownership level of exit funds in a given quarter is the

[13] I use the algorithm described in Koijen et al. (2023). For small funds, when the algorithm does not converge after 200 iterations, I estimate a linear version of equation 1.1, excluding the zero holdings.

share of equity owned in that quarter by funds classified as exit as of $t-1$. The estimated coefficients from the event study are plotted in Figure 1.4. The top panel plots the share of ownership of exit funds around a controversy. The coefficients on $t-4$ to $t-2$ indicate that there is no pre-trend. Then, the coefficient on t is negative and statistically significant at the 1% level, and indicates that exit funds sell 0.15% of the firm's equity after a controversy (7.5% of their position). The coefficients remain negative and significant for the whole year after the controversy and keep on decreasing up until the point where the share of equity owned by exit funds has decreased by almost 20%. The bottom panel of the same figure plots the estimated coefficients from the same exercise, but using all other funds: none of the coefficient is statistically significant. The exit classification thus captures well the divestment behavior of funds when they receive a strong negative CSR signal about a firm.

Correlation with a name-based fund classification. In Appendix 1.B, I show that funds with an explicit focus on S (S-labelled funds such as "Social Choice" or "Socially Aware" funds) are significantly more likely to be exit funds. I also show that being an S-labelled fund predicts a significantly higher β_S, but not any other β from regression 1.1, including β_E and β_G. It also correlates with the weighted average social score of the portfolio but does a better job at predicting an exit behavior following a controversy (Table 1.B3).

Exit pressure at the firm level. In each quarter, I compute the threat of exit faced by firm n from its mutual fund shareholders as

$$\text{Exit}_{n,t} = \sum_i \text{Ownership}_{i,n} \times \mathbf{1}(\underbrace{\text{Exit Fund}_{i,t}}_{\beta_{S,i,t}>0 \text{ \& No index}}) \tag{1.2}$$

where $\text{Ownership}_{i,n}$ is the share of equity of firm n owned by fund i in quarter t.

1.2.3 Measuring Voice

Shareholder ESG activism encompasses observable actions (such as votes or activist campaigns declared through 13D forms) as well as unobservable actions (calls with managers for instance). In this study, I use observable actions to proxy for both observable and non-observable ones. An activist fund is defined as a fund that tends to vote in favor of ESG-related shareholder proposals at Annual General Meetings when the management recommends voting against them. Votes are direct observation and an objective measure of investors' willingness to implement pro-social measures at firms in its portfolio, and are available at high frequency, at

all firms and all mutual funds through the N-PX forms filed at the SEC. Moreover, mutual funds are legally required to vote, which allows me to ignore considerations related to selection into voting (Cvijanovic et al., 2020)

Voting data. I gathered all the N-PX forms filed between 2011 and 2020, for all mutual funds. Not all mutual funds use the same reporting format, and some investors even change the format of their form from one year to another (differences in format can be due to differences in proxy advisors (Shu, 2022). Figure 1.A6 provides an illustration of two formats used by two different investors. I could process the most widely used formats, and I estimate that my sample covers 90% of the votes reported to the SEC during the period. Moreover, I can only observe votes at the CIK level (a typical CIK covers 6 funds in my sample). I then assume that all funds within CIK vote similarly on ESG-related issues.[14] For each CIK each year, I am able to collect: the name of the company at which the vote takes place, its Ticker and CUSIP, the date and type (Annual, Special) of the meeting, the topic of the vote, the recommendation of the management (for/against/withhold), the vote of the funds in a given CIK (for/against/withhold) and who sponsored the proposal (management or shareholder). The overall sample of shareholder proposals covers more than 12,000 meetings, held by almost 3,000 firms in 60 countries, from 2009 to 2020. Appendix 1.D provides additional details on the coverage of the dataset, as well as a comparison with a commercial dataset, the ISS voting data.

Keeping shareholder proposals for which the management recommends voting "against" ensures that shareholders are pressuring the management to adopt pro-social measures against its will.[15] I identify whether each proposal is related to ESG using the detection of keywords. The keywords include, for instance, "gender pay gap", "human rights", and "internet privacy" for the "S" category.[16] I find that 32% of shareholder proposals are ESG related, most of them falling into the "S" category. The share of ESG proposals among shareholder proposals is increasing over time (Figure 1.A7). Panels A and B in Figure 1.A6 show the N-PX reports filed by two investors (MassMutual and Green Century) in 2020, with their votes of two of their funds at Facebook's Annual General Meeting. In particular, items 9 to 11 correspond to S-related proposals, pushed by a shareholder, and opposed by the management.

As I am trying to capture the degree to which a fund threatens the career concerns of the directors, one could argue that votes on directors' elections could be more relevant. I do not use

[14] I find that when several funds in the same CIK vote on the same proposal, they all vote exactly the same more than 90% of the time.

[15] Appendix 1.F proposes an alternative version where the proposals not opposed by the management are included in the calculation.

[16] The full list of keywords can be found in Appendix 1.C.

them for two reasons. First, it is hard to recover the motivation behind a vote against a director. Yi (2021) develops a methodology to recover funds' preferences from their votes, and argues that only few votes against the directors are ESG-motivated. Secondly, there might already be a selection effect through *who* runs for election, as illustrated by the higher resignation rate after a controversy.

Fund voice. In each quarter, I compute a fund's voice score $V_{i,t}$ as the percentage of times the fund's company has voted in favor of the selected proposals over the past year.[17] Coming back to the examples in Figure 1.A6, MassMutual voted against items 9, 10, and 11, and thus scores 0/3 on that AGM. Green Century, on the other hand, voted in favor of all three proposals and receives 3/3. Funds vote on average 53% of the time in favor of S-related shareholder proposals opposed by the management, increasing from 45% in 2013 to almost 60% in 2020. However, there exists a great heterogeneity in the measure, as displayed in Figure 1.3: most funds vote always "for" or always "against" the proposals (middle panel), suggesting that funds have a very strong stance in favor or against pushing ESG proposals at firms in their portfolio. A fund's voice score is stable over time: there is a 0.93 coefficient of correlation between a fund's last quarter score and its current score (p-value $< 1\%$).

Correlation with public engagement status. I test the correlation between my voice score and an observable signal of pro-social engagement: being a participant or an endorser of the *Advance* initiative. It is a UN Principles for Responsible Investment's initiative where institutional investors engage with firms on human rights and social issues. I recover the full list of endorsers and participants from the UN PRI's website (as of September 2023). As the date when each investor joined the initiative is not known, I test the correlation between the status and the voice score of funds at the end of my sample period. I find a 0.12 correlation coefficient between a fund's voice score in April 2020 and its *Advance* status in 2023 (p-value $<1\%$). In addition, I do not find any correlation between the status and funds' exit score, in line with Gibson Brandon et al. (2022) who document that PRI's signatories do not invest more in firms with higher ESG ratings. Figure 1.A9 displays the distribution of exit and voice scores by status.

Voice pressure at the firm level. I define as an activist fund in quarter t a fund with a

[17] This paper does not consider the outcomes of the votes, as shareholder proposals generally fail (Bach and Metzger, 2019), and only half of passed CSR resolutions are actually implemented afterward (Flammer, 2015). I also do not look at actual directors' elections, as votes against directors are rarely motivated by pro-social considerations (Yi, 2021), and activism may rely on unobserved communications (Levit, 2019) that push directors to resign before the end of their term.

$\%_{i,t}$ greater than 85%, which is above the average "for" recommendation from ISS and Glass Lewis. Therefore, a voice fund is any fund that votes more than proxy advisors in favor of pro-social resolutions at the AGMs of firms in its portfolio. I measure the voice pressure from mutual fund shareholders at firm n in quarter t as:[18]

$$\text{Voice}_{n,t} = \sum_i \text{Ownership}_{n,i} \times \mathbf{1}(\underbrace{\text{Voice Fund}_{i,t}}_{\%_{i,t}>85\%}). \tag{1.3}$$

Voice pressure and career concerns. Do firms with higher voice pressure face a greater reelection risk upon the occurrence of a controversy? I run the same event study as in the bottom panel of Figure 1.2 on two sub-samples: firms with above median voice pressure the quarter before the controversy, and firms with below median voice pressure the quarter before the controversy. Figure 1.5 plots the results, showing that the probability that a firm has at least one director resignation in the quarter of the controversy increases by 11pp (or by 85%) at firms with high voice pressure. On the contrary, firms with below median exposure to voice do not have a greater resignation rate after a controversy.[19] I make sure that the effect is not driven by mutual fund ownership by doing the same exercise with the share of equity held by voice mutual funds normalized by total fund ownership (Panel (b) of the same figure). I interpret these results as reflecting the pressure exerted by voice funds on directors' careers when their firm misbehaves.

1.2.4 Stylized Facts on Fund Classification

Figure 1.3 plots the distribution of funds' exit (top panel) and voice scores (middle panel) in the sample, as well as the distribution of four groups: pure exit, pure voice, both exit and voice, and neither exit nor voice funds (bottom panel). The share of exit funds is larger than that of voice funds, and is rising over time (Figure 1.A10). The share of voice funds is relatively stable over time, despite a decrease in recent years. The share of both exit and voice funds is relatively low: only 7% of the funds use both strategies. That can be explained by the fact that those two groups of funds target different companies. I regress $Exit_n$ / $(Exit+Voice)_n$, firm

[18] I match the N-PX data to CRSP using the fund tickers in the header of the forms. Figure 1.A8 provides an example. That allows me to create a ticker-by-year mapping table between the two sources, as CRSP provides a direct mapping between tickers and funds. In the rare cases (<1% of observations) where multiple CIKs are mapped to one fund, I select manually the most relevant fund based on names.

[19] Taking a one-year lag for the voice measure instead of a one-quarter lag does not change the results.

n's average exit pressure normalized by the sum of average exit and voice ownership, on a set of average stock characteristics. The idea is to determine the factors driving the relative exposure to exit and voice funds. Those characteristics are size (log of market capitalization), valuation (book-to-market ratio), Social score, and liquidity (bid/ask spread). The regression also includes industry fixed effects. The results (reported in Table 1.A1) show that larger, cheaper, less socially responsible, and less liquid firms tend to face relatively more voice pressure than exit pressure. These firms are more likely to be mediatized (Engine No 1's campaign against Exxon has been highly discussed in the media, for instance), are cheaper to attack, and have more room for improvement. The crucial role of liquidity echoes the result of Edmans et al. (2013): the incentive to adopt an exit strategy increases with liquidity, as the cost of exit can otherwise be too great.

I also investigate whether the social preferences of a fund's location influence its categorization. I naively regress–in a logit specification–a dummy indicating that a fund is classified as exit in a given quarter on its logged TNA, logged number of holdings, and the percentage of votes in favor of Obama in the 2012 presidential election in the fund's State, and quarter fixed effects. I then do the same with a dummy indicating being classified as a voice fund. Results are reported in Table 1.A2, and show that the political preferences of the State of incorporation do not impact a fund's exit classification. However, Column 2 indicates that a 1pp increase in Obama's votes at the State level increases the probability of being classified as a voice fund by 6%.

A natural question is what motivates funds to adopt one strategy or the other. Funds could adopt an exit strategy for two reasons: 1) they seek to sell a "pro-social portfolio" to investors with aligned values, or 2) they see a higher social score as a signal of good operating performance. If hypothesis 1) holds, exit funds should have a lower flow-performance sensitivity than other funds, as investors do not only seek financial returns and lower or similar returns to other funds. On the contrary, under Hypothesis 2, we could expect the flow-performance sensitivity to be similar to or greater than other funds, and higher returns. Column 1 from Table 1.A3 shows the estimated coefficient from the regressions of flows on lagged return interacted with an indicator for being an exit fund (Column 1) and portfolio and quarter fixed effects. The results are consistent with Hypothesis 1: exit funds receive higher flows–by 5pp per quarter–than other funds (consistently with Van der Beck, 2021), but have a lower flow-performance sensitivity (indicated by a negative coefficient on the interaction term in Column 1). They also earn similar returns as other funds in the same Lipper objective code (Column 3). Regarding the decision to become a voice fund, the motivation could be to invest in stocks that are underpriced due to bad behavior and resell the shares as their social

reputation increases. Consistently with such a view, the interaction between lagged returns and an indicator for being a voice fund has an insignificant coefficient (Column 2), but voice funds tend to earn higher returns (0.15pp per quarter, Column 4).

1.3 Empirical Strategy

I model the occurrence of controversies about firm n as resulting from its exposure to exit and voice in the past quarter, time-invariant firm-specific characteristics and time-varying common characteristics:

$$\text{Controversy}_{n,t} = \text{Exit}_{n,t-1} + \text{Voice}_{n,t-1} + \tilde{\delta}_t + \alpha_n + \tilde{u}_{n,t}. \tag{1.4}$$

As a firm's CSR efforts and its shareholder composition are endogenous, this section details two specifications based on exogenous changes in exit and voice.

1.3.1 Exogenous Variations in Exit and Voice Pressures

To study the impact of voice and exit on firms' behavior, one needs to find changes in firms' exposure to exit and voice unrelated to the change in their anti-social behavior. To that end, I use large redemptions from mutual funds in the spirit of Edmans et al. (2012). Variables construction in this subsection follows Dessaint et al. (2019). Using CRSP data, I compute quarterly outflows from funds as

$$\text{Flows}_{i,t} = \frac{\text{TNA}_{i,t} - \text{TNA}_{i,t-1} \times (1 + \text{Return}_{i,t})}{\text{TNA}_{i,t-1}} \tag{1.5}$$

where $\text{Return}_{i,t}$ is computed as the compounded monthly returns of fund i in quarter t. For all mutual funds for which $\text{Flows}_{i,t} < -0.05$, I compute the *hypothetical* sale of asset n by fund i as

$$MFHS_{n,i,t} = \text{Flows}_{i,t} \times \text{Ownership}_{n,i,t-1}. \tag{1.6}$$

The idea is that when a fund experiences sudden large outflows, it has to liquidate its assets quickly. As the *actual* sales of the fund might be related to firms' CSR, I rely on its *hypothetical* sales, as if the fund liquidated its assets in proportion to their current weights. That leads me to compute the *hypothetical* change in exposure to funds' exit and voice due to large redemptions,

as

$$\begin{cases} Z_{n,t}^{\text{Exit}} = \sum_i MFHS_{n,i,t} \times \mathbf{1}(\text{Exit Fund}_{i,t}) \\ Z_{n,t}^{\text{Voice}} = \sum_i MFHS_{n,i,t} \times \mathbf{1}(\text{Voice Fund}_{i,t}) \end{cases}$$

When facing large redemptions, funds sell in priority their cash holdings over their stocks (Chernenko and Sunderam, 2016), therefore it may take several months before the effect of a large redemption fully materializes into changes in exit and voice at firms in the portfolio.

1.3.2 IV Specification

Starting from Equation 1.4, I remove the time-invariant characteristics by considering the change in the occurrence of controversies over two periods:

$$\begin{aligned} \text{Controversy}_{n,t+2} - \text{Controversy}_{n,t} = \beta_{Exit} \overbrace{\left(\text{Exit}_{n,t+1} - \text{Exit}_{n,t-1}\right)}^{\text{Instrumented by } Z_{n,t}^{Exit}} \\ + \beta_{Voice} \underbrace{\left(\text{Voice}_{n,t+1} - \text{Voice}_{n,t-1}\right)}_{\text{Instrumented by } Z_{n,t}^{Voice}} + \delta_{t+2} + u_{n,t+2}, \end{aligned} \tag{1.7}$$

where the two-period window is optimally chosen based on funds' behavior following large redemptions (Appendix 1.E). When facing large redemptions in period t, fire sales typically last up to the beginning of period $t+1$. The change in exit and voice thus materializes at the end of period $t+1$, determining the firm's behavior in that same period, leading to fewer or more controversies in $t+2$. Finally, in the spirit of shift-share instruments (Borusyak et al., 2022), I instrument the change in exit and voice over three periods by $Z_{n,t}^{\text{Exit}}$ and $Z_{n,t}^{\text{Voice}}$. In Table 1.A4, I show that these shocks are not related to a firm's CSR behavior by regressing the shocks on the occurrence of a controversy in the same quarter (Columns (1) and (2)) or in the past three quarters (Columns 3 and 4), and reporting no statistically significant coefficient.

1.3.3 Event-Study Specification

Not all CSR measures will react at time $t+1$ to a change in behavior at time t: Refinitiv ESG scores, for instance, are updated yearly. Therefore, the timing of the impact of a change in exit or voice on the measure is not straightforward. For that reason, I study separately the influence of exit and voice by considering the most negative $Z_{n,t}^{\text{Exit}}$ and $Z_{n,t}^{\text{Voice}}$ as shocks in an event-study specification. I define as a shock any $Z_{n,t}^{X}$ smaller than $\bar{Z}_{n,t}^{X} - 2\sigma(\bar{Z}_{n,t}^{X})$, where $\bar{Z}_{n,t}^{X}$ is the sample average shock and $\sigma(\bar{Z}_{n,t}^{X})$ the sample standard deviation. That leaves me with 799

unique events for exit and 1,161 for voice (between 2 and 3% of the observations). I consider the occurrence of controversies for the year before and the year after the shock, taking the period -1 as a reference. Such a setup allows me to check for pre-trend and propagation over time of a shock to the shareholding composition. The estimating equation is

$$y_{n,t} = \sum_{\substack{\tau=-4 \\ \tau \neq -1}}^{\tau=4} \left(\beta_\tau \times \text{Shock}^X_{n,t-\tau} \right) + \delta_t + \gamma_n + u_{n,t}, \tag{1.8}$$

where $y_{n,t}$ is a CSR measure, and $\text{Shock}^X_{n,t-\tau}$ is a dummy equal to 1 if $Z^X_{n,t-\tau}$ is smaller than $\bar{Z}^X_{n,t} - 2\sigma(\bar{Z}^X_{n,t})$, for X being exit or voice.

1.4 Results

This section reports the estimated impact of changes in exit and voice on firms' CSR efforts, as well as several robustness checks.

1.4.1 IV Results

Table 1.3 reports the coefficients from the instrumental variable estimation of the change in controversies on the instrumented changes in exit and voice.[20] The bottom panel of the table provides first-stage statistics, showing that the instruments satisfy the conditions for strong instruments (Stock and Yogo, 2002, Kleibergen and Paap, 2006).[21] [22] Column 1 indicates that a change in exit has no statistically significant impact on the change in the occurrence of controversies, a result robust to the inclusion of control variables (Column 2). On the contrary, the estimated coefficient on the change in voice is negative and statistically significant. The effect is economically large: a standard deviation increase in voice decreases the dependent variable by 28% of a standard deviation.[23] Table 1.A6 illustrates the need for an instrument: Column 1 reports the coefficients from a regression of the change in the occurrence of controversies on a change in voice, and Column 2 reports the same coefficients when the change in voice is instrumented. The "naive" regression reports a positive but statistically insignificant coefficient: an increase in voice pressure *correlates* with more controversies in the future,

[20] The tables do not report the R-squared, as it is not informative in an IV setting (Wooldridge, 2013).

[21] I report the Kleibergen-Paap statistic for regressions with multiple endogenous regressors, and the effective F-statistic (Olea and Pflueger, 2013) for regressions with only one endogenous regressor, as suggested by Andrews et al. (2018).

[22] The first-stage coefficients can be found in Table 1.A5.

[23] Alternatively, Logit and Poisson estimates (Table 1.A7) indicate that a 1pp increase in voice decreases the probability of a controversy by between 10 and 20%.

indicating that activist funds tend to target firms with deteriorating behavior. Instrumenting the change in voice flips the sign.

Media coverage. Can the results above point to a decrease in firms' media coverage? I rule out this alternative by regressing the change in the count of non-ESG news as the dependent variable. The results are reported in Table 1.4. Column 1 reports the estimated coefficients when taking the log count of news as the dependent variable, and Column 2 the count normalized by the firm size. In both cases, there is no statistically significant relationship between exit, voice, and media coverage.

Placebo controversies. I test whether the voice pressure leads to an actual improvement in firms' CSR efforts, or just better public relations management. I run the same analysis with the change in the occurrence of "stale" controversies. I define as a stale controversy any controversy for which the underlying event is more than 90 days old. Results are reported in Table 1.A8 and show that neither the instrumented change in exit nor the instrumented change in voice has a significant impact on the occurrence of such news.

Window-dressing. Parise and Rubin (2023) document that ESG funds tend to strategically hold more responsible portfolios just before mandated disclosures. Such behavior could lead me to underestimate the effect of the threat of exit, as some funds classified as exit funds would hold a pro-social portfolio only before the disclosures. While I cannot completely rule out the concern that some funds identified as exit funds are window-dressers, I run the main analysis based on the sample of funds that voluntarily report their holdings at the monthly frequency (as opposed to quarterly), as there should be less suspicion of window-dressing for those funds. Table 1.A9 reports the results, and shows no significant difference with the results based on the full sample.

"Stable" exit funds. To avoid any concern regarding the persistence of the exit classification could affect the results, I focus on stable exit funds, meaning funds that are classified as exit since the first quarter of 2013 and remain so until the end of the sample (116 funds) or that when they become exit, remain exit until the end of the sample (423 funds). Regressing the change in the occurrence of controversies on the instrumented change in exit pressure using stable exit funds only does not change the results. The estimated coefficient goes from 0.11 to 0.08, with a p-value ranging from 0.45 to 0.68 (Table 1.A10).[24]

[24]Results using only funds that are classified as exit in 2013 and remain so until the end of the sample are similar, but lead to a relatively weak instrument (F-stat of 23).

Alternative exit and voice thresholds. Are the main results sensitive to a change in the definitions of exit and voice funds? In Appendix 1.B, I re-estimate model 1.7 using an exit threshold ranging from 0% to 1.5%: the estimated coefficients are plotted in Figure 1.B3 and show that as the threshold increases, the estimated coefficient does not materially change. In Appendix 1.F, I re-estimate model 1.7 using a voice threshold ranging from 50% to 95%: as the threshold increases, the estimated coefficient becomes more negative and increases in statistical significance (Figure 1.F2): the coefficient goes from -0.5 to -1.5, and its p-value from 18% to 3%. I find that when choosing a threshold (strictly) below 65%, the estimated coefficient on the instrumented change in voice is negative but insignificant. When the threshold is between 65 and 75%, the coefficient is negative and statistically significant at the 10% level. Finally, any threshold at or above 75% leads to a negative and statistically significant (at the 5% level) coefficient.

1.4.2 Event-Study Results

Controversies. Figure 1.6 plots the estimated coefficients for a shock to exit (solid, red lines) or voice (dashed, blue lines) on the occurrence of controversies one quarter later. Each coefficient can thus be interpreted as the probability of observing a controversial behavior, materializing in a public controversy the following quarter. The left panel shows no impact of a negative shock to exit on the occurrence of controversies. The right panel, on the other hand, shows that when voice funds are forced to fire-sell their assets, firms in their footprint are more likely to misbehave 1, 2, and 4 quarters after the shock. The non-statistically significant for periods -4 to -2 confirm that voice shocks are not predicted by controversies.

I also make sure that the results for voice are robust to explicitly take into account the staggered treatment (Sun and Abraham, 2021), the absence of control variables, and the use of *Quarter* × *Industry* fixed effects. The estimated coefficients are plotted in Figure 1.A12, and show that none of these alternatives significantly change the main results.

Other visible CSR efforts. Voice funds' influence extends to other measures of CSR efforts: NGO campaigns, Refinitiv's social score, donations to revenue, and board gender diversity, as depicted in Figure and 1.7. Board gender diversity is measured by a dummy equal to one if the board has no women. Following an exogenous decrease in voice pressure, the occurrence of NGO campaigns against a firm increases, its social score decreases by 2.5% in the following three quarters, donations to revenue decrease by 10% the next quarter (statistically significant

at the 10% level), and board diversity deteriorates significantly and permanently. The null result for exit is attenuated when considering the Social score (Figure 1.A11): a negative shock to exit pressure leads to a 2% decrease in social score the following quarter. However, the effect is short-lived, as the Social score goes back to its pre-shock level two quarters after the shock. There is no effect of exit on NGO campaigns, donations, and gender board diversity.

Price impact of exit and voice funds' redemptions. I investigate whether: *i)* these exogenous changes in exit and voice pressures are large enough to have a price impact, *ii)* exogenous changes in exit and voice pressures have a different impact on stock prices. One may worry that the results above are driven by a stock price effect, and that exit and voice funds might have a different price impact. I compute each stock's daily *Abnormal Returns* using a Fama and French (2015) 5-factor model around quarters of negative exit and voice shocks. I then compute their *Cumulative Abnormal Returns* starting 63 days (one quarter) before and plot their estimation on Figure 1.A13. The estimated CARs indicate that both exit and voice funds' redemptions do have a price impact: an extreme exogenous decrease in exit or voice pressure leads to a negative CAR of between 1 and 1.5% over a quarter.[25] The difference in price impact between exit and voice funds is statistically significant, ruling out Hypothesis *ii.*

Accounting performance measures. Figure 1.A14 reports the estimated coefficients from similar event studies using accounting performance measures (alternatively, the profit margin, return on equity, and return on assets) as dependent variables. None of these measures seem to be affected by changes in exit and voice pressures.

1.4.3 Does Exit Reinforce Voice?

I now try to evaluate the extent to which voice needs the threat of exit to be effective. To that end, I run the same analysis using pure index funds (identified by their *index fund flag* "D" in CRSP). These funds can only use voice, as the threat of exit of an S&P500 fund at Microsoft, for instance, is probably not credible. To make sure that the threat of exit is not credible, I restrict the sample of firms to firms in either the S&P500 or the S&P400. Results are reported in Table 1.A11: as in the main specification, an increase in voice pressure decreases significantly the occurrence of social controversies. The magnitude is even greater: almost two times larger than when considering all funds. A possible explanation is that index funds are on average

[25]This price impact is significantly lower than the quarterly price impact of 10% reported in Dessaint et al. (2019), as they used all mutual funds, and not a subset of them like in this paper.

six times larger than other funds, making them more likely to be blockholders. In addition, they are more likely to be shareholder of a firm for a long time: they currently still hold 66% of stocks in their investment universe, against 50% for other funds. In other words, they have exited less than $\frac{1}{3}$ of the firms they were holding 3 years ago, against up to $\frac{1}{2}$ for the other funds.

1.5 Identifying the Motives Behind Large Redemptions: Natixis Trading Losses

The empirical strategy in this paper relies on large investor redemptions from US mutual funds, but what drives such redemptions? I exploit as a natural experiment the large trading losses from a French investment bank on its derivatives business in Korea, which forced it to liquidate a sizeable share of its US ETF holdings.

1.5.1 Background

On December 18, 2018, the French investment bank Natixis reported "non-recurring losses" of more than USD 300 million on its Asian equity derivatives business.[26] The derivatives in question were mostly Korean autocallables that underperform when the underlying index does badly, and the Kospi, the country's main stock market index, lost almost 18% between the end of March 2018 and January 2019 (the S&P500 lost 4% during the same period). At the same time, the bank's US ETF holdings, as reported in the 13F forms, almost halved, while that of other French institutions remained stable.[27] This section uses these large cuts as a shock to US mutual funds unrelated to firms' CSR. More specifically, firms with a high exposure to voice funds owned by Natixis before the trading losses see a significant decrease in their voice pressure over the year of the trading losses (Figure 1.A15). The estimated coefficients indicate that if Natixis owns 10% of a voice fund that owns 10% of firm n's equity, firm n's voice pressure is expected to decrease by 0.5pp after Natixis' trading losses.

[26] `https://natixis.groupebpce.com/wp-content/uploads/2022/08/2019.02.12_2018_results_natixis_pr.pdf`

[27] Natixis is identified by manager number 11607 (manager name "NATIXIS"), and ETF investments are identified as having their CUSIP in CRSP. I do not consider, in the main text, other institutions related to Natixis (such as Natixis Assurances), for two reasons. First, these other institutions are way smaller (their aggregate holdings represent less than 10% of Natixis'), and they reportedly did not scale down their US investments during the period, indicating that they were not hit by the trading losses.

1.5.2 Empirical Setting

I measure the exposure of each fund to Natixis by the percentage of fund shares held by Natixis, as reported in the 13F data at the end of Q2 2018: $\text{NatExpo}_{i,18:Q1}$. Then, in a similar fashion as before, I compute the exogenous change in a firm's exposure to funds' voice due to Natixis trading losses in Q2 (as if Natixis liquidated its entire portfolio):[28]

$$Z_{\text{Voice},n,18:Q2} = \sum_i \text{NatExpo}_{i,18:Q1} \times \text{Ownership}_{i,n,18:Q1} \times \mathbf{1}(\text{Voice Fund}_{i,18:Q1}),$$

subsetting on firms for which $\sum_i \text{NatExpo}_{i,18:Q2} \times \text{Ownership}_{i,n,18:Q2} > 2.5\%$. This filter keeps 646 of the firms in the sample but ensures that $Z^{\text{Voice}}_{n,18:Q3}$ is a strong instrument for the change in voice. I run:

$$\begin{aligned} \text{Controversy}_{n,19:Q1} - \text{Controversy}_{n,18:Q2} = & \overbrace{\text{Voice}_{n,18:Q4} - \text{Voice}_{n,18:Q1}}^{\text{Instrumented by } Z^{\text{Voice}}_{n,18:Q2}} \\ & + \text{Sector}\times\text{State}_n + u_{n,19:Q1}. \end{aligned} \tag{1.9}$$

1.5.3 Results

Table 1.A12 reports the results. It indicates that the F-statistic for the instrument in the first stage is well above 100, and thus satisfies the condition for strong instruments. The estimated coefficient for the change in voice is negative and statistically significant, and its sign and magnitude (Column 1) are robust to the inclusion of controls (Column 2). The magnitude of the effect is smaller than in the main specification (a 1pp increase in voice pressure is associated with a decrease in the dependent variable of 14% of a standard deviation, against 28% in the main specification). One explanation relies on the fact that this subset of firms has a significantly higher rate of staggered boards, which, as shown in Section 1.6, hinder the effect of voice. 50% of firms in the sub-sample have such a structure, against 36% in other firms. The difference in means is statistically significant at the 1% level. When removing firms with staggered boards from the sample, the estimated coefficient drops to -1.6, in line with the main results. However, the sample becomes too small to have a significant first-stage (F-stat of 8).

[28] I do not consider the change in exit pressure due to the fact that most ETFs owned by Natixis before the losses are index funds.

1.6 Mechanism

This section explores the incentives that executives and directors respond to when pressured by shareholders to adopt more pro-social practices.

1.6.1 Exit Mechanism

If firms' executives and directors want to retain their shareholders, they could respond more to exit pressure in two cases: 1) when their cost of capital is high, and 2) when their executives have private incentives to keep a high valuation of the firm.

Cost of capital. Firms with higher cost of capital may be more responsive to funds' threat of exit to keep their cost of equity as low as possible. Appendix 1.G tests that assumption by calculating three different versions of firms' Weighted Average Cost of Capital (WACC) based, alternatively, on the CAPM, the Fama-French 3-factor model, and the Gordon growth model. It also considers firms' Standard & Poor's long-term credit rating. For each (lagged) proxy for the cost of capital, I divide the sample in two (above median or below median cost of capital, or speculative bond rating and investment grade), and run the following specification:

$$\text{Controversy}_{n,t+2} - \text{Controversy}_{n,t} = \beta_{Exit} \overbrace{\left(\text{Exit}_{n,t+1} - \text{Exit}_{n,t-1}\right)}^{\text{Instrumented by } Z_{n,t}^{Exit}} + \delta_{t+2} + u_{n,t+2}. \tag{1.10}$$

In all cases, firms with a higher cost of capital do not respond more to the threat of exit.

CEO wealth-performance sensitivity. I test whether executives with more personal exposure to their firm's stock price are more likely to comply with their shareholders' pro-social requests. I recover firms' CEO wealth-performance sensitivity from Alex Edmans' website (Edmans et al., 2009). To avoid endogeneity, I compute the average CEO WPS of each firm between 2000 and 2012, and I run, on each WPS quartile sub-sample, equation 1.10. Table 1.5 reports the results. The coefficient on the instrumented change in exit is not statistically different from zero for quartiles 1 to 3 (Columns 1 to 3), but the coefficient becomes more negative as we move from the first quartile to the second. Moving to the quartile with the highest WPS (Column 4), the coefficient on the instrumented change in exit is negative and statistically significant: a 1pp increase in the share of equity owned by exit funds significantly decreases the occurrence of controversies two quarters later. Firms in that quartile do not exhibit major differences with firms in other quartiles in terms of baseline characteristics, as

highlighted in the *Comparability* panel of the same table. Therefore, the threat of exit seems to be effective only at firms with high CEO WPS. In addition, I also run an alternative specification with an interaction term:

$$\text{Controversy}_{n,t+2} - \text{Controversy}_{n,t} = \beta_{\text{Exit}} \times Z_{n,t}^{\text{Exit}} + \beta_{\text{WPS}} \left(Z_{n,t}^{\text{Exit}} \times \text{WPS}_n \right) + \delta_{t+2} + u_{n,t+2}, \tag{1.11}$$

where *WPS* is the average past CEO WPS, standardized for readability.[29] Table 1.A13 reports the estimated coefficients. As before, β_{Exit} is positive and insignificant, but the coefficient on the interaction term, β_{WPS} is negative and significant. Its magnitude indicates that a 1% increase in exit pressure at firms with a one standard deviation WPS above the mean reduces corporate controversies by 10%. As a robustness to the results above, I also run the same regression with WPS defined as a dummy for each quartile of the WPS distribution. The coefficients are reported in Column 2 of Table 1.A13, and are in line with previous results.

1.6.2 Voice Mechanism

I turn to the mechanism through which voice funds can incentivize firms to adopt more pro-social behavior. Consistent with the hypothesis that the leadership's career concerns drive pro-social effort, I show that firms' directors comply with their shareholders' requests to ensure their reelection. Contrarily to the threat of exit, this strategy is effective at all firms, as the threat is universal.

Board structure. An important feature of US companies' boards is whether they are staggered. A staggered board structure means that directors serve overlapping term lengths, such that not all directors are reelected at the same time. Such a board structure makes board takeovers less likely. In such a structure, directors should be less willing to listen to shareholders, and the effect of voice should be diminished. Using data from Refinitiv, around 41% of the firms in the sample have a staggered board. I run the following specification on the two sub-samples of firms with and without a staggered board:

$$\text{Controversy}_{n,t+2} - \text{Controversy}_{n,t} = \beta_{Voice} \overbrace{\left(\text{Voice}_{n,t+1} - \text{Voice}_{n,t-1} \right)}^{\text{Instrumented by } Z_{n,t}^{Voice}} + \delta_{t+2} + u_{n,t+2}. \tag{1.12}$$

Results are reported in Columns 3 and 4 in Table 1.6. As expected, the effect of voice is strong and statistically significant among firms *without* a staggered board, and indistinguishable from

[29] Note that the term WPS_n alone does not appear as it is fixed over time.

zero among other firms.

Exogenous variations in board renewal rate. I further investigate the role of upcoming elections on the relationship between voice and controversies by exploiting within-firm time variation in board renewal rate. At firms with a staggered board, the percentage of directors seeking reelection can vary from one year to another. For instance, Tesla's board had 10 members in 2020, divided into three classes with overlapping three-year terms: if three of them end their term in 2020 (30%), 4 directors (40%) will have to be reelected in 2021 or 2022.[30] As less than half of the firms in the sample have a staggered board and the BoardEx data covers only 1,335 firms in the sample, further subsetting the sample based on board renewal leads my instrument to be weak.[31] Thus, I exploit the time-varying nature of the board renewal rate within 507 firms with a staggered structure and non-missing board data by running:

$$\begin{aligned}\text{Controversy}_{n,t+2} - \text{Controversy}_{n,t} = {} & Z^{\text{Voice}}_{n,t} \times 1\left(\text{Board Renewal Rate Above } \textit{Reference}_{n,t}\right) \\ & + Z^{\text{Voice}}_{n,t} + 1\left(\text{Board Renewal Rate Above } \textit{Reference}_{n,t}\right) \\ & + \delta_t + u_{n,t+2},\end{aligned} \tag{1.13}$$

where the *Reference* is, alternatively, the firm mean, median, and previous year's board renewal rate. Table 1.7 reports the result. Column 1 indicates that the raw effect of a voice shock on controversies is insignificant, in line with the results above. Interestingly, the coefficient on the dummy indicating a greater than usual board renewal rate is negative and statistically significant, showing that firms behave better when more board directors seek reelection, regardless of their shareholder composition. The coefficient on the interaction term between the (standardized) shock to voice and the dummy indicating a greater than usual board renewal rate is negative and statistically significant at the 5% level. I interpret this result as evidence that within firms, when more directors than usual are seeking reelection, firms are more prone to be disciplined by voice funds: a one percentage point increase in voice pressure at firms with one standard deviation higher board renewal rate decreases the number of controversies over the next year by 18%.

Voice spillovers. Finally, I show that an activist campaign against a director at a firm spillovers to other firms through what I call a *threat of voice*. To that end, I exploit an episode of a successful campaign against the reelection of a director and show that firms in the same

[30] See Tesla's 2020 Proxy Statement: `bit.ly/3YCmERS`

[31] Running model 1.12 on that sub-sample leads to an F-statistic of 3.

industry and with a high level of common ownership experienced fewer controversies in the following quarters. In June 2017, Seaworld Chairman since 2010 David D'Alessandro failed to be reelected at the board, collecting only 47% of the casted votes, falling short of the required 50%. Years of tense public relations and degraded reputation since the documentary *Blackfish*, which highlighted the firm's bad treatment of whales and orcas, culminated in 2017 with the death of *Blackfish*'s flagship orca, Tilikum, excessive executive pay, and the opening of two federal investigations over disclosures and trading around the documentary's release.[32] Figure 1.A16 shows an example of Peta's anti-Seaworld protest launched in California after Tilikum's death. Activist funds voted massively against the reelection of the director (99% of the activist shares voted against), in an episode labeled as a "shareholder revolt" by the Financial Times.[33] I investigate how this episode propagated across Seaworld's activist funds' footprint. I measure firms' exposure to Seaworld as:

$$\text{Exposure to Seaworld}_n = \sum_i \text{Ownership}_{i,n} \times \mathbf{1}(\text{Own Seaworld}_i) \times \mathbf{1}(\text{Voice Fund}_i),$$

meaning, the share of firm n's equity owned by voice funds also shareholders of Seaworld. As Seaworld's episode happened at the end of the second quarter of 2017, and as the outcome of the vote was –arguably– unpredictable, one can expect firms to adapt their behavior in the third quarter, resulting in fewer controversies in the fourth quarter. One can also expect that the effect is stronger at firms in the same industry as Seaworld. In order to test these assumptions, I run the following regression:

$$\begin{aligned}\text{Controversy}_{n,17:Q4} - \text{Controversy}_{n,17:Q2} = {} & \text{Exposure to Seaworld}_{n,17:Q1} \\ & + \text{Exposure to Seaworld}_{n,17:Q1} \times \mathbf{1}(\text{Same Industry}_n) \\ & + (\text{Industry}\times\text{State})_n + u_{n,17:Q4},\end{aligned} \tag{1.14}$$

where *Same Industry* is defined as having the same Global Industry Classification Standards (GICS) 6-digit Industry classification as Seaworld. 83 firms are classified as such (mainly hotels, restaurants, and leisure).[34] Table 1.A14 reports the results. Column 1 reports the estimated coefficient from the exposure to Seaworld alone, without interaction. The coefficient is negative and statistically significant at the 5% level, indicating that firms more connected

[32] https://www.nytimes.com/2017/06/30/business/killer-whales-aside-seaworlds-shareholders-are-mistreated.html

[33] https://www.ft.com/content/1d523502-86e8-300a-a005-665bb3ec0822

[34] I do not use the TRBC sector classification like before because it is much broader: 507 firms would be classified as being in the same sector as Seaworld.

to Seaworld through common ownership improved their behavior compared to other firms. When interacting the exposure to Seaworld with a dummy equal to one if the two firms are in the same industry (Column 2), we can see that the effect is driven by firms in the same industry: the coefficient on the interaction term is negative and statistically significant at the 1% level, tripling the baseline effect. These results indicate that activist investors do not need to launch a campaign at a firm to improve its behavior: their actions at other firms spillover across their portfolio.

1.6.3 Discussion

This paper measures the level of exit and voice pressures that firms face from their mutual fund shareholders, and draws a causal link between these pressures, firms' pro-social efforts, and managerial incentives. Social controversies allow to capture firms' observable and non-observable efforts and trigger immediate exit and voice punishments. The above results show that the *threat* of these punishments only leads to efforts when managerial incentives are personal.

The fact that executives improve their behavior only when their wealth is highly dependent on their firm's stock price, and not when the cost of capital is high could be interpreted in two ways. Either executives do not care about their firm's cost of equity, or the price impact of pro-social investors' exit is short. In the first case, what could matter is the threat of a higher cost of debt: it has been shown, for instance, that more polluting firms generally have more tangible capital–that can be used as collateral–and rely more on debt financing (Papoutsi et al., 2021). That channel is corroborated by Figure 1.A2, showing that the cost of debt (measured by the average interest rate) does not respond to controversies. In the second case, in line with Berk and van Binsbergen (2021), managers could care mostly about the short-term decrease in their wealth, and not about the increase in the cost of capital if they do not plan to raise funds in the short term. In that sense, Figure 1.A1 seems to indicate that a firm's valuation goes back to normal 6 quarters after a controversy. Finally, CSR could be seen as a luxury far from constrained firms' considerations.

Regarding voice, this paper emphasizes that activist investors do not seek to improve firms' pro-sociality by increasing the chances of success of S-related shareholder proposals. This paper considers funds' votes as a signal to firms in their portfolio that they are ready to publicly confront the board on social topics. Such a threat pushes unfavoured directors to resign and not face a reelection vote. Most of the effect captured could be due to behind-the-doors pressures that are rarely observed by the researcher and signaled through the votes. The fact that one's

reelection is more effective than threatening their compensation aligns with recent evidence on CEO compensation: Edmans et al. (2023) survey executives and report that they care more about their career and reputation than their salary.

1.7 Conclusion

How can shareholders promote pro-social behavior at firms they hold in their portfolios? This paper evaluates the effectiveness of the threat of exit (divestment) and voice (activism) in making firms act more pro-socially. It confirms the theoretical prediction of Broccardo et al. (2022) that voice is more effective than exit and shows that these strategies are effective only when they are aligned with strong managerial incentives.

Using a sample of almost 2,000 US mutual funds, I identify exit funds using their portfolio holdings. I recover their preference for pro-social stocks using the "demand system approach to asset pricing" and define an exit fund as a fund that, all else equal, invests more in companies with a higher Social score. Then, I identify voice funds based on their votes at companies' Annual General Meetings. In order to capture *activism*, I focus on S-related shareholder proposals opposed by management. I show that these funds push directors to resign in case of misbehavior. To identify the influence of different fund types on firms' pro-social behavior, I use plausibly exogenous changes in funds' influence due to large redemptions.

The main result is that only voice funds successfully discipline firms' behavior. When voice funds are forced to sell 1% of a firm's equity, the probability that the firm faces a social controversy increases by 10 to 20%. The result is robust to alternative specifications and alternative measures of visible CSR efforts. I also exploit large trading losses from a French investment bank that forced it to cut its US ETF holdings as a shock to firms' voice pressure and find similar results. I do not find evidence that firms respond to the shareholders' threat of exit to have a lower cost of capital. I find that exit only works among firms whose executives have a high wealth-performance-sensitivity, and that voice is more effective when directors seek reelection.

Taken together, my results shed light on the optimal shareholders' strategy to influence firms, and on the incentives that managers and directors respond to. In addition, this paper develops a portable framework to infer mutual funds' influence on firms and could be applied in contexts other than Corporate Social Responsibility.

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Table 1.1: Summary statistics – firms

Variable	Mean	Median	Q1	Q3	SD
i. Characteristics					
Market Cap (USD B)	10.06	2.46	0.96	7.16	32.24
Total Assets (USD B)	10.44	2.27	0.81	6.58	43.46
Book Equity (USD B)	3.36	0.89	0.37	2.32	12.40
Dividends to Book	0.04	0.02	0	0.06	0.06
Profitability	0.87	0.62	0.39	1.02	0.85
Beta	1.19	1.15	0.81	1.53	0.57
Investment	8.97	5.26	-1.01	14.15	18.65
ii. ESG characteristics					
Environmental Score	18.96	3.15	0	34.15	25.74
Social Score	30.13	29.03	0	48.48	25.70
Governance Score	35.13	35.49	0	60.28	29.08
Quarter with at least one controversy (0/1, ×100)	2.37	0	0	0	15.21
Quarter with at least one NGO campaign (0/1, ×100)	0.95	0	0	0	9.74
Donations to revenue (%)	3.58	0.96	0.38	2.04	13.90
No women on board (0/1, ×100)	13.93	0	0	0	34.63
% of women on board	17.02	16.67	11.11	25.00	10.79
iii. Mutual funds ownership					
Overall fund ownership (%)	19.84	18.81	14.14	24.06	8.32
Exit fund ownership (%)	3.04	2.28	1.11	4.15	2.77
Voice fund ownership (%)	5.93	5.45	1.87	8.85	4.91
Exit shock (%)	-0.04	-0.01	-0.05	0	0.09
Voice shock (%)	-0.05	-0.01	-0.03	0	0.18
iv. Governance					
Staggered board (0/1, ×100)	41.38	0	0	100	49.25
% of directors facing reelection within a year	77.59	100.00	37.50	100.00	31.27
CEO Wealth-Performance Sensitivity	27.12	8.73	4.66	20.18	53.46
CEO compensation with ESG target (0/1, ×100)	29.02	0.00	0.00	100.00	45.39
N = 1,910					
Quarterly data from 2013 to 2020					

Note: This table displays summary statistics for firms in the sample. Stock characteristics, including ESG scores, are from Refinitiv. Investment is defined as the annual log growth rate of assets. The variable *Non-ESG news* and *Controversy* are constructed using Ravenpack data. NGO campaigns data from Koenig (2017). Mutual fund ownership variable are constructed using data from CRSP. Details about the construction of the exit and voice pressures can be found in the main text. The variable *Staggered board* is from Refinitiv. *Distance to elections* is constructed using data from ISS. *CEO wealth-performance sensitivity* is defined as the change in CEO compensation for a 100% change in firm value (Edmans et al., 2009) and is from Alex Edmans' website.

Table 1.2: Summary statistics – funds

Variable	Mean	Median	Q1	Q3	SD
i. Holdings characteristics					
Market value of US stocks held (USD B)	3.04	0.40	0.10	1.41	20.01
Number of stocks currently held	149.96	65.00	40	148.00	229.41
Stocks in investment universe	260.34	144.00	82.00	318.00	319.37
Share of Equity in portfolio (%)	97.49	98.48	96.64	99.60	3.15
ii. Flows and returns					
Quarterly net flow (% of TNA)	0.82	-1.22	-4.16	2.66	12.01
Quarterly return (%)	2.80	3.51	0.07	6.90	7.78
iii. Exit and voice characteristics					
Pure index fund (%)	24.91	0	0	0	43.25
Exit score (β_S, ×100)	-0.29	-0.16	-0.94	0.46	1.25
Exit fund (%)	28.94	0	0	100	45.35
Voice score (%)	53.09	57.34	16.79	83.24	35.46
Voice fund (%)	23.80	0	0	0	42.58
N = 1,995					
Quarterly data from 2013 to 2020					

Note: This table displays summary statistics for funds used in the analysis. Funds in the sample are not specialized in one sector, hold at least 20 US stocks in their portfolio, and could have their voting data retrieved from the N-PX files. Fund holdings data are from CRSP. *Stocks in the investment universe* is the number of stocks currently held or held in the last 11 quarters. The exit variable is estimated using model 1.1, and the voice variable is computed using mutual fund votes data from the N-PX forms filed at the Securities and Exchange Commission. Quarterly net flows are computed as in Dessaint et al. (2019).

Table 1.3: The impact of changes in exit and voice on the occurrence of social controversies

Dependent Variable:	$\text{Controversy}_{n,t+2}$ - $\text{Controversy}_{n,t}$	
Model:	(1)	(2)
Variables		
Instrumented Change in Exit	0.237	0.220
	(0.186)	(0.186)
Instrumented Change in Voice	-1.32**	-1.32**
	(0.612)	(0.610)
Change in Total Assets		-0.010
		(0.012)
Change in Investment		-0.005
		(0.008)
Change in Social Score		0.023
		(0.014)
Fixed-effects		
Quarter	✓	✓
Fit statistics		
Observations	37,480	37,480
Kleibergen-Paap Statistic	21.442	21.332

Note: This table reports estimated coefficients from model 1.7, the regression of a change in the occurrence of controversies, on *Instrumented Change in Exit* and *Instrumented Change in Voice*, respectively the change in the share of equity owned by exit and voice funds, instrumented by the hypothetical change in those shares due to large redemptions, and controls. All regressions include quarter fixed effects. Details on the construction of the variables can be found in the main text. Controversies are defined based on Ravenpack data. The sample covers 1,910 US firms from 2013 to 2020. Stock characteristics from Refinitiv. Clustered (cusip) standard-errors in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

Table 1.4: A media coverage effect? The impact of exit and voice on the number of non-ESG news

Dependent Variables:	$\log(\text{Count}_{n,t+2})$-$\log(\text{Count}_{n,t})$	$\frac{\text{Count}_{n,t+2}}{\text{Assets}_{n,t+2}} - \frac{\text{Count}_{n,t}}{\text{Assets}_{n,t}}$
Model:	(1)	(2)
Variables		
Instrumented Change in Exit	-0.043	-0.064
	(0.545)	(0.103)
Instrumented Change in Voice	-0.663	0.076
	(0.824)	(0.062)
Change in Total Assets	-0.121***	-0.045***
	(0.026)	(0.009)
Change in Investment	0.103***	0.008*
	(0.019)	(0.005)
Change in Social Score	0.132***	0.0008
	(0.034)	(0.004)
Fixed-effects		
Quarter	✓	✓
Fit statistics		
Observations	36,992	37,043
Kleibergen-Paap Statistic	20.039	20.078

Note: This table reports estimated coefficients from the regression of a change in the count of non-ESG news on *Instrumented Change in Exit* and *Instrumented Change in Voice*, respectively the change in the share of equity owned by exit and voice funds, instrumented by the hypothetical change in these shares due to large redemptions, and controls. All regressions include quarter fixed effects. Details on the construction of the variables can be found in the main text. News data from Ravenpack. The sample covers 1,910 US firms from 2013 to 2020. Stock characteristics from Refinitiv. Clustered (cusip) standard-errors in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

Table 1.5: The impact of exit on the occurrence of controversies at firms with high CEO wealth-performance sensitivity

Dependent Variable:	$\text{Controversy}_{n,t+2}$ - $\text{Controversy}_{n,t}$			
Lagged *WPS* quartile:	Q1	Q2	Q3	Q4
Model:	(1)	(2)	(3)	(4)
Variables				
Instrumented Change in Exit	0.446*	-0.186	0.992	-0.891**
	(0.255)	(0.454)	(0.924)	(0.405)
Change in Total Assets	-0.027	-0.009	0.060*	-0.026
	(0.025)	(0.028)	(0.031)	(0.023)
Change in Investment	0.030	-0.005	-0.045*	-0.007
	(0.020)	(0.028)	(0.023)	(0.022)
Change in Social Score	-0.009	0.014	0.028	0.022
	(0.021)	(0.031)	(0.038)	(0.033)
Fixed-effects				
Quarter	✓	✓	✓	✓
Comparability				
Firms	301	301	300	300
Average log Total Assets	21.76	21.97	22.00	21.54
Average Investment (×100)	7.81	6.50	7.61	8.57
Average Social Score	28.22	35.84	36.26	31.80
Fit statistics				
Observations	6,888	6,639	7,225	7,040
Effective F-statistic	34.086	40.041	13.616	46.813

Note: This table reports the estimated coefficients from the regression of a change in the occurrence of controversies on the change in the share of equity owned by divestor funds instrumented by the hypothetical change in that share due to large redemptions (*Instrumented Change in Exit*) on four sub-samples defined by their past (from 2010 to 2012) average Scaled CEO wealth-performance sensitivity (*WPS*, from Edmans et al., 2009), and controls. All regressions include quarter fixed effects. Details on the construction of the variables can be found in the main text. Controversies are defined based on Ravenpack data. Stock characteristics from Refinitiv. The sample covers 1,110 US firms from 2013 to 2020. Clustered (cusip) standard-errors in parentheses. The *Effective F-statistic* is the Olea and Pflueger (2013) first-stage F-statistic. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

Table 1.6: The impact of voice on the occurrence of controversies, by board structure

Dependent Variable:	$\text{Controversy}_{n,t+2}$ - $\text{Controversy}_{n,t}$	
Sample:	Non-staggered board	Staggered board
Model:	(1)	(2)
Variables		
Instrumented Change in Voice	-3.37***	-0.470
	(1.25)	(1.27)
Change in Total Assets	-0.016	-0.010
	(0.034)	(0.022)
Change in Investment	-0.011	-0.010
	(0.022)	(0.012)
Change in Social Score	0.034	0.016
	(0.025)	(0.021)
Fixed-effects		
Quarter	✓	✓
Comparability		
Firms	933	567
Average log Total Assets	21.26	22.26
Average Investment (×100)	9.05	7.17
Average Social Score	26.41	38.63
Fit statistics		
Observations	15,058	10,442
Effective F-statistic	13.697	37.239

Note: This table reports estimated coefficients from the regression of a change in the occurrence of controversies on the change in the share of equity owned by activist funds instrumented by the hypothetical change in that share due to large redemptions (*Instrumented Change in Voice*) and controls, for different sub-samples. Column 1 focuses on firms with a non-staggered board, and Column 2 focuses on firms with staggered board. Column 3 focuses on firms in which all directors are ending their term within a year (based on BoardEx data), while Column 4 focuses on firms in which not all directors are ending their term soon. All regressions include quarter fixed effects. Regressions 3 and 4 also include *Staggered board* fixed effects. Details on the construction of the variables can be found in the main text. Controversies are defined based on Ravenpack data. Stock and board characteristics from Refinitiv. The original sample covers 1,910 US firms from 2013 to 2020. Clustered (cusip) standard-errors in parentheses. The *Effective F-statistic* is the Olea and Pflueger (2013) first-stage F-statistic. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

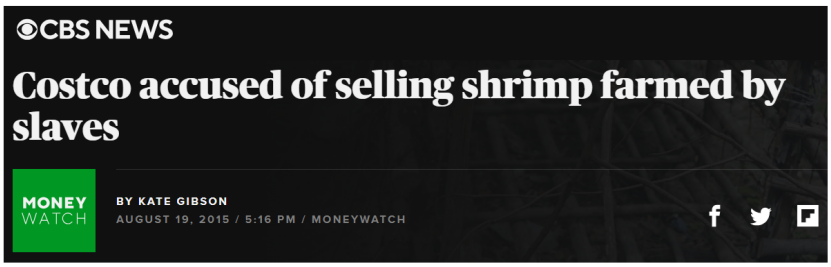
Table 1.7: Exogenous changes in board renewal rate and the impact of voice on controversies

Dependent Variable:	$Controversy_{n,t+2}$ - $Controversy_{n,t}$		
Reference is firm:	Median	Mean	Previous Year
Model:	(1)	(2)	(3)
Variables			
Shock to Voice	0.031	0.046	0.027
	(0.029)	(0.037)	(0.040)
% of Directors Seeking Reelection Above *Reference*	-0.011**	-0.007*	-0.014**
	(0.004)	(0.004)	(0.005)
Shock to Voice × % of Directors Seeking Reelection Above *Reference*	-0.120**	-0.113**	-0.127**
	(0.051)	(0.049)	(0.062)
Change in Total Assets	-0.023	-0.023	-0.004
	(0.024)	(0.024)	(0.032)
Change in Investment	-0.007	-0.008	-0.025
	(0.020)	(0.020)	(0.027)
Change in Social Score	0.008	0.008	0.002
	(0.027)	(0.027)	(0.048)
Fixed-effects			
Quarter	✓	✓	✓
Fit statistics			
Observations	6,047	6,047	4,191
R^2	0.00748	0.00727	0.00889

Note: This table reports estimated coefficients from model 1.13, the regression of a change in the occurrence of controversies, on *Shock to Voice*, the the hypothetical change in the share of equity owned by activist funds due to large redemptions, a dummy equal to one if the board renewal rate in that year is above the firm's average (Column 2), median (Column 2), or that in the previous year (Column 3), the interaction between the two, and controls. All regressions include quarter fixed effects. Details on the construction of the variables can be found in the main text. Controversies are defined based on Ravenpack data. The sample covers 526 US firms from 2013 to 2020. Stock characteristics from Refinitiv. Clustered (cusip) standard-errors in parentheses.
Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

Figure 1.1: Examples of social controversies

(a) Example 1: Costco



(b) Example 2: Starbucks



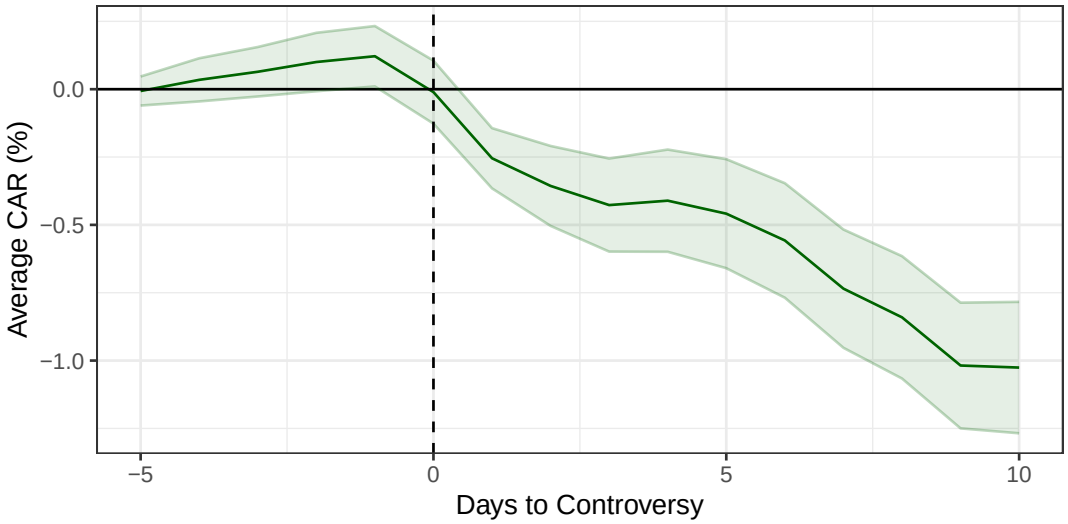
(c) Example 3: Google



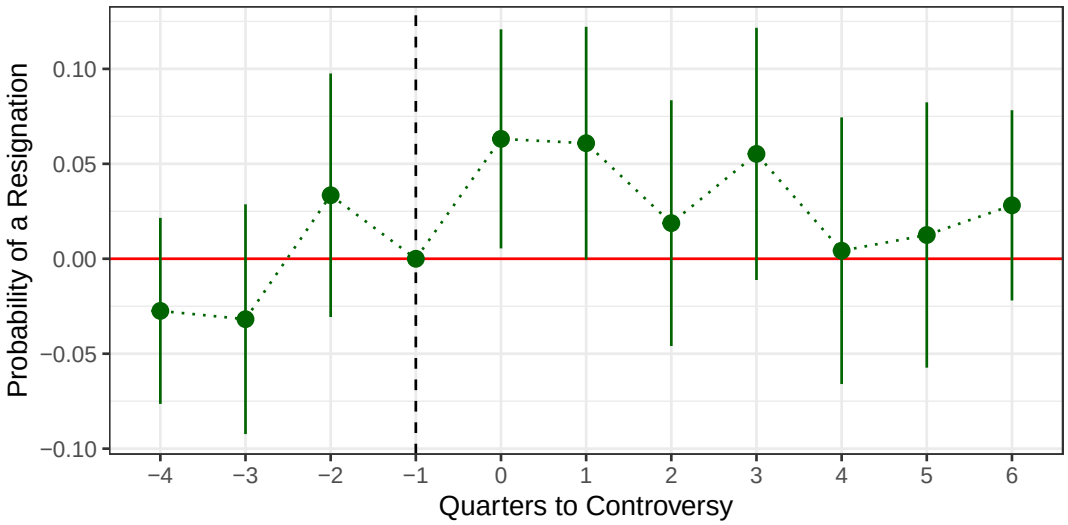
Notes: This figure displays three examples of social controversies. The top panel is a screenshot from a CBS news article published on August 19, 2015. The middle panel is a screenshot from a New York Times' article published on April 15, 2018. The bottom panel is a screenshot from a Financial Times' article published on October 28, 2020.

Figure 1.2: Shareholders' reaction to a social controversy

(a) Average Cumulative Abnormal Returns around a controversy

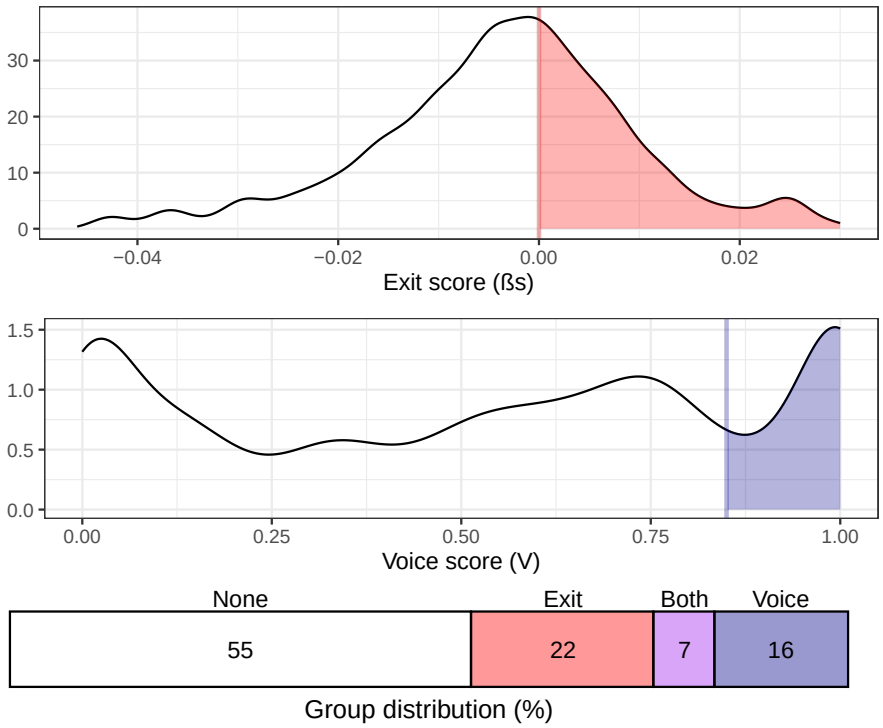


(b) Occurrence of a director or officer resignation around a controversy



Notes: The top panel displays the Cumulative Average Abnormal Returns around the outbreak of a Social public controversy, from 5 days before to 10 days after its publication. The abnormal returns are computed using a Fama and French (1993) 3-factor model. The solid line represents the estimated coefficient, and the shaded area represents the 95% confidence interval. Stock returns and betas are from CRSP. Portfolio returns and the risk-free rate are from Kenneth French's website. The sample covers 1,910 US firms from 2013 to 2020. The bottom panel displays the estimated coefficients from an event study using a logistic regression, with the occurrence of a director or officer resignation as the dependent variable. The coefficients of interest are the time dummies that indicate the number of quarters to the closest Social controversy. The time dummy -1 is used as a reference. The regression also includes firm and quarter fixed effects. The 95% confidence interval is constructed using standard errors clustered at the firm level. Director resignation data is from Audit Analytics. The sample covers 643 firms from 2013 to 2020.

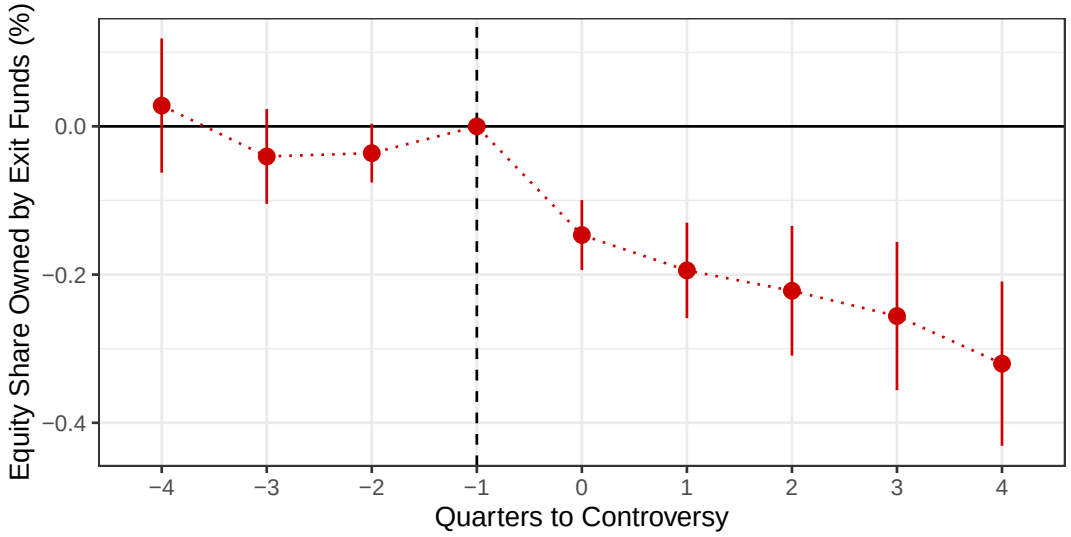
Figure 1.3: Distribution of exit score, voice score, and fund types



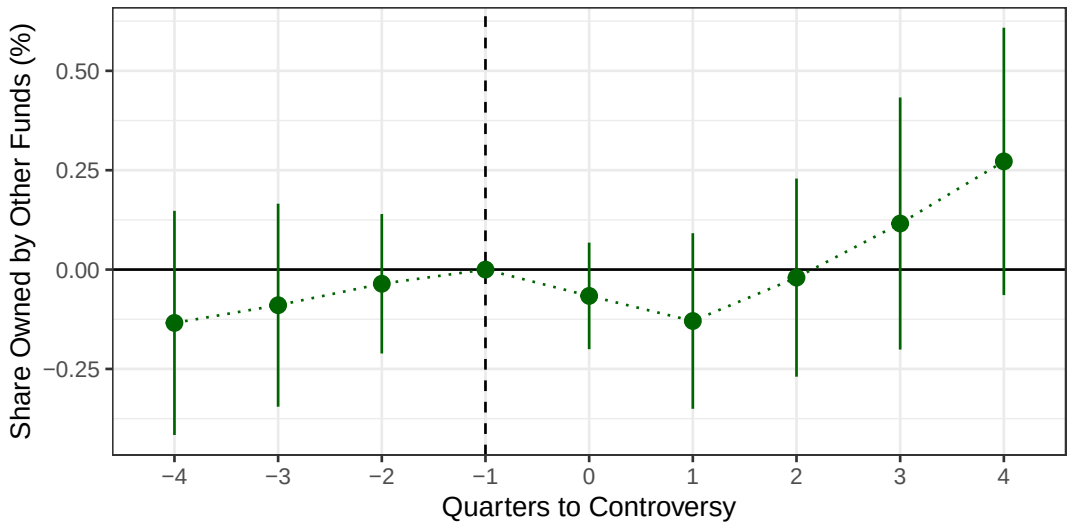
Notes: This figure displays distributions of funds' exit score (top panel, excluding index funds), funds' voice score (middle panel, including all funds), and fund groups (bottom panel, including all funds). The vertical red (blue) line in the top (respectively, middle) panel indicates the threshold for being considered an exit (voice) fund. Based on 1,995 funds between 2013 and 2020. Fund holdings data from CRSP. Funds voting data based on the N-PX files gathered from the SEC website. Details on the construction of the exit and voice scores can be found in the main text.

Figure 1.4: Fund divestment after a controversy

(a) Exit funds' ownership around a controversy



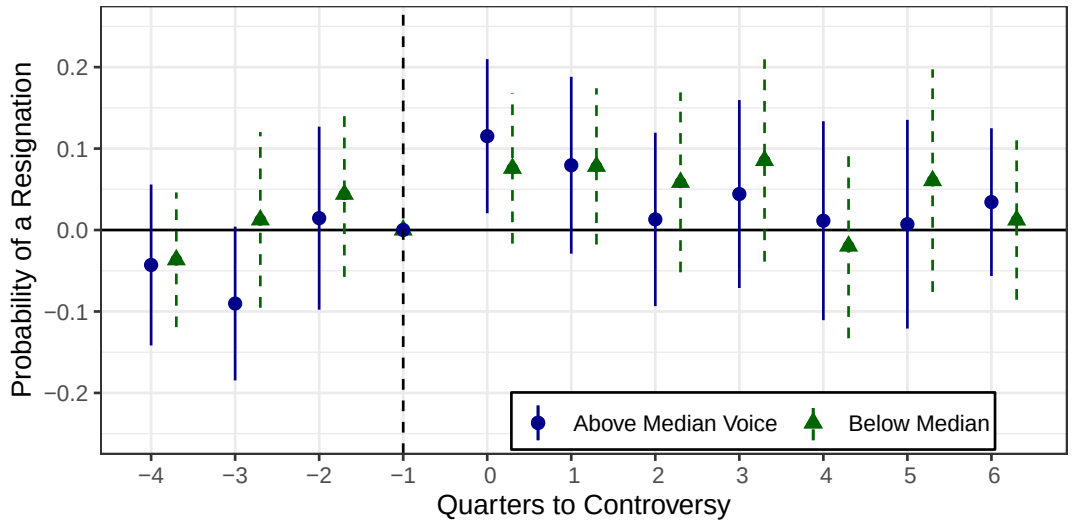
(b) Non-exit funds' ownership around a controversy



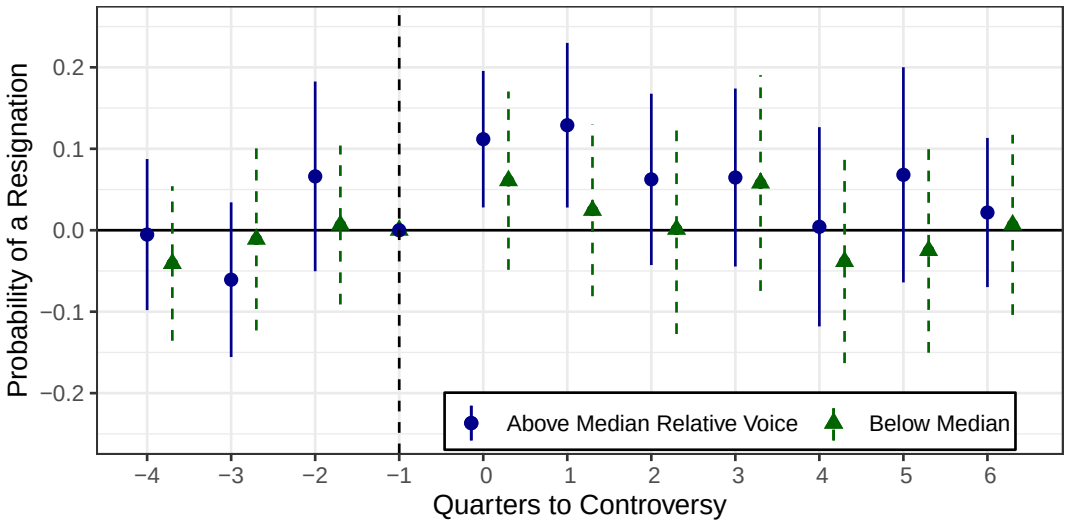
Notes: This figure reports the estimated coefficients of an event study of the share of equity owned by exit funds (as of period $t-1$, top panel) or non-equity funds (as of period $t-1$, bottom panel) around a controversy. The regressions also include time and firm fixed effects. The 95% confidence intervals are constructed using standard errors clustered at the firm level. Controversies are constructed from Ravenpack data. Portfolio holding data from CRSP. The sample covers 1,950 US firms from 2013 to 2020.

Figure 1.5: Director and officer resignations after a controversy at firms with high voice pressure

(a) Voice pressure defined as percentage of total ownership

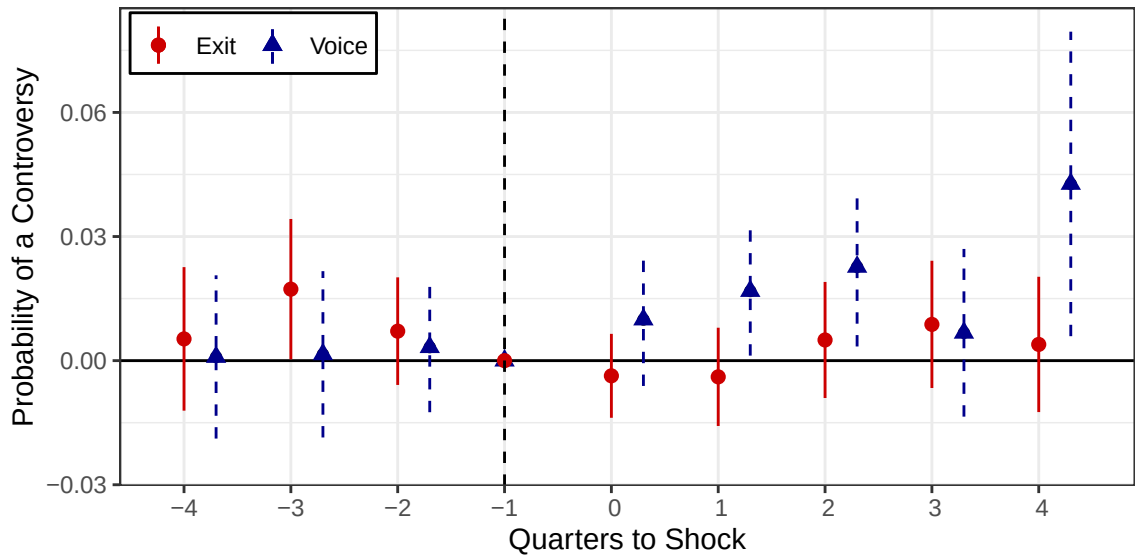


(b) Voice pressure normalized by fund ownership



Notes: This figure plots the equivalent regression of the bottom panel of Figure 1.2 on two sub-samples: firms with voice pressure above median (blue dots), and firms with voice pressure below median (green triangles). Voice pressure is defined as the percentage of a firm's equity owned by voice funds in panel (a), and the same percentage normalized by total fund ownership in panel (b). Director resignation data is from Audit Analytics. Social controversies are constructed from Ravenpack data. The sample covers 643 firms from 2013 to 2020.

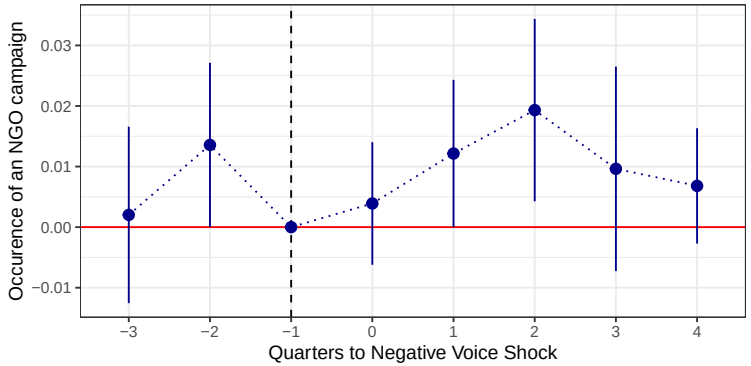
Figure 1.6: The impact of negative shocks to exit and voice pressures on the occurrence of social controversies



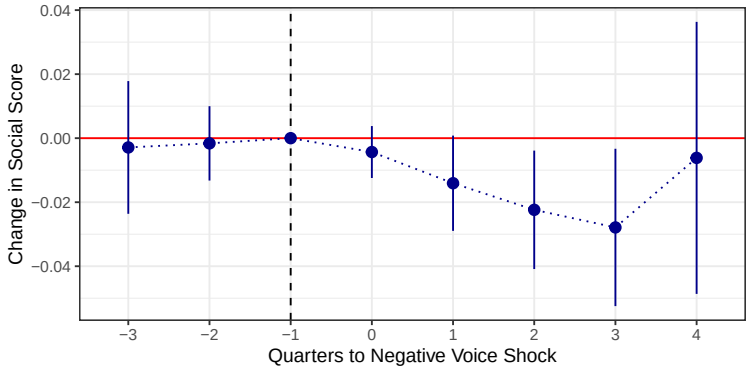
Notes: This figure displays the estimated coefficients from an event study of the occurrence of a controversy in the next period on a time dummy interacted with the occurrence of a large negative exit shock (solid, red line), and negative voice shock (dashed, blue line). The regressions also control of the log of total assets, investment, profitability, dividends to book equity, beta, a dummy indicating an ESG compensation policy, and firm and quarter fixed effects. The 95% confidence interval is constructed from standard errors clustered at the firm level. Accounting data from Refinitiv. Controversies are constructed from Ravenpack data. The sample covers 1,950 US firms from 2013 to 2020.

Figure 1.7: The impact of negative shocks to voice pressure on different measures of Corporate Social Responsibility

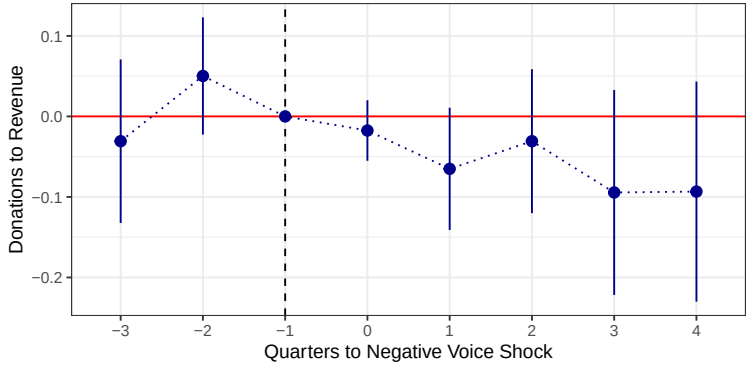
(a) Occurrence of an NGO campaign



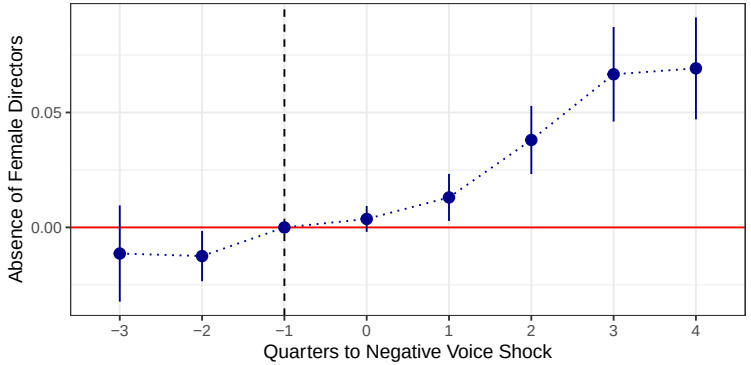
(b) Log Social score



(c) Log Donations to revenue



(d) Absence of female director



Notes: This figure displays the estimated coefficients from four event studies. The dependent variable is, alternatively, the occurrence of a negative NGO campaign next period (panel a), the log of the Social score (panel b), the log of donations to revenue (panel c), and a dummy indicating that there is no women on the board (panel d). Data on NGO campaigns from Koenig (2017). Data for the other dependent variables from Refinitiv. The regressions include time and firm fixed effects. The standard errors used to compute the 95% confidence interval are clustered at the firm level. A voice shock is defined as an expected change in voice due to funds' large redemptions two standard deviations away from the sample mean. The sample covers 1,910 US firms from 2013 to 2020.

Appendix to Chapter 1

1.A Omitted Tables and Figures

Table 1.A1: The correlation between exit, voice, and stock characteristics

Dependent Variable:	$100 \times \frac{\text{Exit}}{\text{Exit+Voice}}$
Variables	
Size *(log MC)*	-2.08**
	(0.881)
Cheapness *(BTM)*	-3.04***
	(0.829)
Social Score	1.51**
	(0.743)
Liquidity *(−1 ×Spread)*	2.10**
	(0.833)
Fixed-effects	
Industry	✓
Fit statistics	
Observations	1,858
R^2	0.05991

Note: This table reports estimated coefficients from the regression of the share of exit funds ownership scaled by the share of exit and voice funds ownership, on its average log market capitalization, book-to-market ratio, social score, and (minus one times) average bid/ask spread. The regression includes industry fixed effects. The dependent variable is multiplied by 100 for readability, and independent variables are standardized for comparibility. Details on the construction of the variables can be found in the main text. The sample covers 1,858 US firms from 2013 to 2020. Stock characteristics from Refinitiv. Robust standard-errors in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

Table 1.A2: States' political leaning and domestic fund classification

Dependent Variables:	Exit	Voice
Model:	(1)	(2)
Variables		
log(TNA)	-0.032*	0.061*
	(0.016)	(0.034)
log(Holdings)	-0.177***	-0.035
	(0.047)	(0.072)
Share of Obama votes	-0.002	0.059***
	(0.004)	(0.009)
Fixed-effects		
Quarter	✓	✓
Fit statistics		
Observations	120,415	120,415
Pseudo R^2	0.01031	0.02470

Note: This table reports estimated coefficients from the logit regressions of a dummy indicating whether a fund is classified as an *exit* fund (Column 1) or a *voice* fund (Column 2), on its logged Total Net Assets, logged number of holdings, the share of votes in favor of Obama in the 2012 presidential election in the fund's State, and quarter fixed effects. The sample covers 1,995 funds from 2013 to 2020. Fund data from CRSP. Election data from the *American Presidency Project*. Robust standard-errors in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

Table 1.A3: Fund classification, flows, and performance

Dependent Variables:	$\text{Flow}_{i,t}$		$\text{Adjusted Return}_{i,t}$ (%)	
Model:	(1)	(2)	(3)	(4)
Variables				
$\text{Return}_{i,t-1}$	0.511***	0.496***		
	(0.032)	(0.032)		
$\text{Exit}_{i,t}$	0.048**			
	(0.022)			
$\text{Return}_{i,t-1} \times \text{Exit}_{i,t}$	-0.049**			
	(0.022)			
$\text{Voice}_{i,t}$		0.018		
		(0.023)		
$\text{Return}_{i,t-1} \times \text{Voice}_{i,t}$		-0.003		
		(0.022)		
$\text{Exit}_{i,t-1}$			0.055	
			(0.037)	
$\text{Voice}_{i,t-1}$				0.143**
				(0.062)
Fixed-effects				
Quarter	✓	✓	✓	✓
Portfolio	✓	✓	✓	✓
Fit statistics				
Observations	36,626	36,626	36,923	36,923
R^2	0.23785	0.23820	0.09567	0.09577

Note: This table reports estimated coefficients from the regression of contemporaneous fund flows on lagged returns interacted with an indicator for being an exit fund (Column 1) or a voice fund (Column 2), and of contemporaneous adjusted returns (return minus the average return from funds with the same Lipper objective code) on an indicator for lagged exit (Column 3) or voice (Column 4). The regressions include portfolio and quarter fixed effects. The variables *Flow*, *Return* and *Adjusted Return* are winsorized at the 1st and 99th percentile. Details on the construction of the variables can be found in the main text. The sample covers 1,995 US funds from 2013 to 2020. Fund data from CRSP. Standard-errors clustered at the portfolio level in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

Table 1.A4: The impact of controversies on exogenous shocks to exit and voice

Dependent Variables:	$Z_{n,t}^{Exit}$		$Z_{n,t}^{Voice}$	
Model:	(1)	(2)	(3)	(4)
Variables				
$Controversy_{n,t}$	0.180	0.149	0.118	0.066
	(0.160)	(0.167)	(0.133)	(0.141)
$Controversy_{n,t-1}$		0.039		-0.039
		(0.170)		(0.149)
$Controversy_{n,t-2}$		-0.098		-0.200
		(0.188)		(0.161)
Fixed-effects				
Quarter	✓	✓	✓	✓
Firm	✓	✓	✓	✓
Fit statistics				
Observations	52,863	48,555	52,772	48,477
Adjusted R^2	0.62579	0.63878	0.63443	0.63973

Note: This table reports estimated coefficients from the regression of shocks to exit (Columns 1 and 2) and voice (Columns 3 and 4), on the occurrence of controversies. All regressions include quarter and firm fixed effects. Details on the construction of the variables can be found in the main text. Controversies are defined based on Ravenpack data. The sample covers 1,910 US firms from 2013 to 2020. Clustered (cusip) standard-errors in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

Table 1.A5: First stage: the impact of shocks to exit and voice on changes in exit and voice

Dependent Variables:	$\text{Exit}_{n,t+1}$ - $\text{Exit}_{n,t-1}$		$\text{Voice}_{n,t+1}$ - $\text{Voice}_{n,t-1}$	
Model:	(1)	(2)	(3)	(4)
Variables				
$Z^{\text{Exit}}_{n,t}$	4.78***	4.74***		
	(0.265)	(0.263)		
$Z^{\text{Voice}}_{n,t}$			1.32***	1.31***
			(0.195)	(0.196)
Change in Total Assets		-0.006***		-0.010***
		(0.002)		(0.003)
Change in Investment		0.080		0.006
		(0.118)		(0.150)
Change in Social Score		0.015***		0.003**
		(0.002)		(0.001)
Fixed-effects				
Quarter	✓	✓	✓	✓
Fit statistics				
Observations	39,419	39,419	39,419	39,419
R^2	0.05813	0.06114	0.63781	0.63925

Note: This table reports estimated coefficients from the first stage of model 1.7, the regression of *Change in Exit* (Columns 1 and 2) and *Change in Voice* (Columns 3 and 4), respectively the change in the share of equity owned by divestor and activist funds, on the hypothetical change in those shares due to large redemptions (Z^{Exit} and Z^{Voice}), and controls. All regressions include quarter fixed effects. Details on the construction of the variables can be found in the main text. Stock characteristics data from Refinitiv. The sample covers 1,910 US firms from 2013 to 2020. Clustered (cusip) standard-errors in parentheses. *Change in Investment* and *Change in Social Score* are divided by 100 for readability. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

Table 1.A6: Bias when the change in voice is not instrumented

Dependent Variable:	$\text{Controversy}_{n,t+2}$ - $\text{Controversy}_{n,t}$	
Change in Voice is:	Not Instrumented	Instrumented
Model:	(1)	(2)
Variables		
Change in Voice	0.052	-1.28**
	(0.037)	(0.609)
Change in Total Assets	0.003	-0.011
	(0.009)	(0.012)
Change in Investment	-0.005	-0.005
	(0.008)	(0.008)
Change in Social Score	0.021	0.026*
	(0.014)	(0.014)
Fixed-effects		
Quarter	✓	✓
Fit statistics		
Observations	37,480	37,480
Effective F-statistic	–	43.299

Note: This table reports estimated coefficients from the regression of a change in the occurrence of controversies, on *Change in Voice*, the change in the share of equity owned by activist funds (Column 1), and the same variable instrumented by the hypothetical change in that share due to large redemptions (Column 2). Both regressions include quarter fixed effects. Details on the construction of the variables can be found in the main text. Controversies are defined based on Ravenpack data. The sample covers 1,910 US firms from 2013 to 2020. Stock characteristics from Refinitiv. Clustered (cusip) standard-errors in parentheses. *Change in Social Score* is divided by 100 for readability. The *Effective F-statistic* is the Olea and Pflueger (2013) first-stage F-statistic. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

Table 1.A7: Estimation of the impact of an exogenous change in exit and voice pressures on the occurrence of social controversies, using different specifications

Dependent Variable:	Controversy$_{n,t+2}$					
Specification:	OLS		Logit		Poisson	
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Shock to Exit	0.011*	0.011*	0.950	0.961	0.862	0.870
	(0.006)	(0.006)	(0.764)	(0.769)	(0.674)	(0.677)
Shock to Voice	-0.016***	-0.016***	-0.204**	-0.200**	-0.113**	-0.110**
	(0.006)	(0.006)	(0.088)	(0.088)	(0.055)	(0.055)
Log Total Assets	0.013*	0.013*	0.533**	0.546**	0.385**	0.398**
	(0.007)	(0.007)	(0.254)	(0.258)	(0.181)	(0.184)
Investment	-0.006	-0.006	-0.185	-0.184	-0.099	-0.097
	(0.007)	(0.007)	(0.305)	(0.308)	(0.229)	(0.232)
Social Score	-0.015	-0.015	-0.543	-0.560	-0.258	-0.284
	(0.013)	(0.013)	(0.711)	(0.722)	(0.496)	(0.503)
Environmental Score	-0.002	-0.002	-0.152	-0.153	-0.184	-0.181
	(0.011)	(0.012)	(0.645)	(0.651)	(0.483)	(0.487)
Governance Score	0.012	0.012	0.804*	0.808*	0.576*	0.578*
	(0.008)	(0.008)	(0.421)	(0.426)	(0.303)	(0.307)
Lagged Mutual Fund Ownership	0.025	0.025	3.12**	3.14**	2.78**	2.80**
	(0.017)	(0.017)	(1.37)	(1.38)	(1.19)	(1.20)
Controversy$_{n,t}$		-0.012		-0.134		-0.092
		(0.018)		(0.163)		(0.102)
Fixed-effects						
Quarter	✓	✓	✓	✓	✓	✓
Cusip	✓	✓	✓	✓	✓	✓
Fit statistics						
Observations	36,257	36,257	8,272	8,272	8,273	8,273
R^2	0.26306	0.26318	–	–	–	–
Pseudo R^2	–	–	0.20127	0.20148	0.15643	0.15658

Note: This table reports estimated coefficients from OLS (Columnes 1 and 2), Logit (Columns 3 and 4), and Poisson (Columnes 5 and 6) regressions of *Controversy*$_{n,t+2}$, a dummy indicating the occurrence of a controversy two quarters later, on the hypothetical change in firm *n*'s exit and voice pressures (*Shock to Exit* and *Shock to Voice*, respectively) due to large fund redemptions, controls, lagged mutual fund ownership, and firm and quarter fixed effects. The lagged mutual ownership is included as the sum of shares does not equal 1, and the model is not in differences (Borusyak et al., 2022). Models 2, 4, and 6 also include a dummy indicating the occurrence of a controversy in the current quarter. Clustered (cusip) standard-errors in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

Table 1.A8: The impact of exit and voice pressures on placebo controversies

Dependent Variable:	$\text{Placebo}_{n,t+2}$ -$\text{Placebo}_{n,t}$	
Model:	(1)	(2)
Variables		
Instrumented Change in Exit	0.009	0.021
	(0.104)	(0.105)
Instrumented Change in Voice	-0.273	-0.270
	(0.426)	(0.426)
Change in Total Assets		0.006
		(0.010)
Change in Investment		0.010
		(0.007)
Change in Social Score		-0.005
		(0.011)
Fixed-effects		
Quarter	✓	✓
Fit statistics		
Observations	37,480	37,480
Kleibergen-Paap Statistic	21.442	21.332

Note: This table reports estimated coefficients from the regression of a change in the count of *stale* controversies on *Instrumented Change in Exit* and *Instrumented Change in Voice*, respectively the change in the share of equity owned by exit and voice funds, instrumented by the hypothetical change in these shares due to large redemptions, and controls. Stale controversies are defined as social controversies about an event that happened more than 90 days before the publication of the article. All regressions include quarter fixed effects. Details on the construction of the variables can be found in the main text. News data from Ravenpack. The sample covers 1,910 US firms from 2013 to 2020. Stock characteristics from Refinitiv. Clustered (cusip) standard-errors in parentheses. *Change in Social Score* is divided by 100 for readability. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

Table 1.A9: The impact of exit and voice pressures on the occurrence controversies, using funds less likely to be window-dressers

Dependent Variable:	$\text{Controversy}_{n,t+2}$ -$\text{Controversy}_{n,t}$	
Model:	(1)	(2)
Variables		
Instrumented Change in Exit	0.209	0.195
	(0.177)	(0.176)
Instrumented Change in Voice	-1.92**	-1.92**
	(0.841)	(0.840)
Change in Total Assets		-0.007
		(0.013)
Change in Investment		-0.014
		(0.009)
Change in Social Score		0.009
		(0.012)
Fixed-effects		
Quarter	✓	✓
Fit statistics		
Observations	30,506	30,506
Kleibergen-Paap Statistic	21.442	21.332

Note: This table reports estimated coefficients from the regression of a change in controversies on *Instrumented Change in Exit* and *Instrumented Change in Voice*, respectively the change in the share of equity owned by exit and voice funds, instrumented by the hypothetical change in these shares due to large redemptions, and controls. The regressions only use funds that report their holdings monthly to the SEC, as those funds are less likely to be "window-dressers". All regressions include quarter fixed effects. Details on the construction of the variables can be found in the main text. News data from Ravenpack. The sample covers 1,910 US firms from 2013 to 2020. Stock characteristics from Refinitiv. Clustered (cusip) standard-errors in parentheses. *Change in Social Score* is divided by 100 for readability. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

Table 1.A10: Stability of the exit fund classification, and the impact of exit on controversies

Dependent Variable:	$\text{Controversy}_{n,t+2}$-$\text{Controversy}_{n,t}$	
Exit pressure measured using	Stable exit funds	
Model:	(1)	(2)
Variables		
Instrumented Change in Exit	0.083	0.087
	(0.188)	(0.189)
Change in Total Assets		0.0009
		(0.009)
Change in Investment		-0.004
		(0.008)
Change in Social Score		0.0002
		(0.0001)
Fixed-effects		
Quarter	✓	✓
Fit statistics		
Observations	41,105	41,105
Effective F-statistic	39.096	39.562

Note: This table reports estimated coefficients from the regression of a change in the occurrence of controversies, on *Instrumented Change in Exit*, and controls. *Exit* is measured either as the share of firm *n*'s equity owned by stable exit funds, defined as funds that remain classified as exit after their first exit classification (539 funds). All regressions include quarter fixed effects. Details on the construction of the variables can be found in the main text. Controversies are defined based on Ravenpack data. The sample covers 1,910 US firms from 2013 to 2020. Stock characteristics from Refinitiv. Clustered (cusip) standard-errors in parentheses. The *Effective F-statistic* is the Olea and Pflueger (2013) first-stage F-statistic. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

Table 1.A11: Voice without exit: the impact of index funds' voice on controversies on firms in the S&P 400 or 500

Dependent Variable:	Controversy_{t+2} - Controversy_t	
Model:	(1)	(2)
Variables		
Change in Voice	-2.27**	-2.26**
	(1.09)	(1.05)
Change in Total Assets		-0.106
		(0.068)
Change in Investment		0.074*
		(0.041)
Change in Social Score		0.002*
		(0.0008)
Fixed-effects		
Quarter	✓	✓
Fit statistics		
Observations	11,364	11,364
Effective F-statistic	9.2238	9.4169

Note: This table reports estimated coefficients from the regression of the change in occurrence of controversies (Columns 1 and 2) on the change in the share of equity owned by voice index funds instrumented by the hypothetical change in that share due to large redemptions (*Instrumented Change in Voice*). All regressions include quarter fixed effects. Details on the construction of the variables can be found in the main text. Controversies are defined based on Ravenpack data. The sample covers the US firms in either the S&P400 or the S&P500, from 2013 to 2020. Stock characteristics from Refinitiv. Clustered (cusip) standard-errors in parentheses. The *Effective F-statistic* is the Olea and Pflueger (2013) first-stage F-statistic. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

Table 1.A12: The impact of voice on the occurrence controversies, using funds owned by Natixis, following Natixis' trading losses

Dependent Variable:	$\text{Controversy}_{n,2019Q1}$ - $\text{Controversy}_{n,2018Q2}$	
Model:	(1)	(2)
Variables		
Instrumented Change in Voice	-0.225***	-0.246**
	(0.056)	(0.084)
Change in Investment		0.076
		(0.094)
Change in Total Assets		-0.124**
		(0.042)
Change in Social Score		-0.001
		(0.001)
Fixed-effects		
Sector × State	✓	✓
Fit statistics		
Observations	646	646
Effective F-statistic	21.385	22.649

Note: This table reports estimated coefficients from model 1.9, the regression of a change in occurrence of controversies, on the change in the share of equity owned by activist funds instrumented by the hypothetical change in that share due to large redemptions from funds in Natixis' portfolio (*Instrumented Change in Voice*), and controls. All regressions include sector-by-state fixed effects. Details on the construction of the variables can be found in the main text. Controversies are defined based on Ravenpack data. The sample covers 646 US firms. Stock characteristics from Refinitiv. Clustered (Industry) standard-errors in parentheses. The *Effective F-statistic* is the Olea and Pflueger (2013) first-stage F-statistic. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

Table 1.A13: The impact of exit at firms with high CEO WPS - interacted version

Dependent Variable:	$\text{Controversy}_{n,t+2}$ - $\text{Controversy}_{n,t}$	
Model:	(1)	(2)
Variables		
Shock to Exit	0.230	1.62
	(1.19)	(1.13)
Shock to Exit×WPS	-0.975**	
	(0.388)	
Shock to Exit×WPS:Q2		-1.66
		(2.10)
Shock to Exit×WPS:Q3		0.724
		(3.27)
Shock to Exit×WPS:Q4		-4.36**
		(1.83)
Change in Total Assets	-0.001	-0.001
	(0.013)	(0.013)
Change in Investment	-0.006	-0.006
	(0.012)	(0.012)
Change in Social Score	0.016	0.016
	(0.015)	(0.015)
Fixed-effects		
Quarter	✓	✓
Fit statistics		
Observations	27,792	27,792
Adjusted R^2	0.00017	0.00017

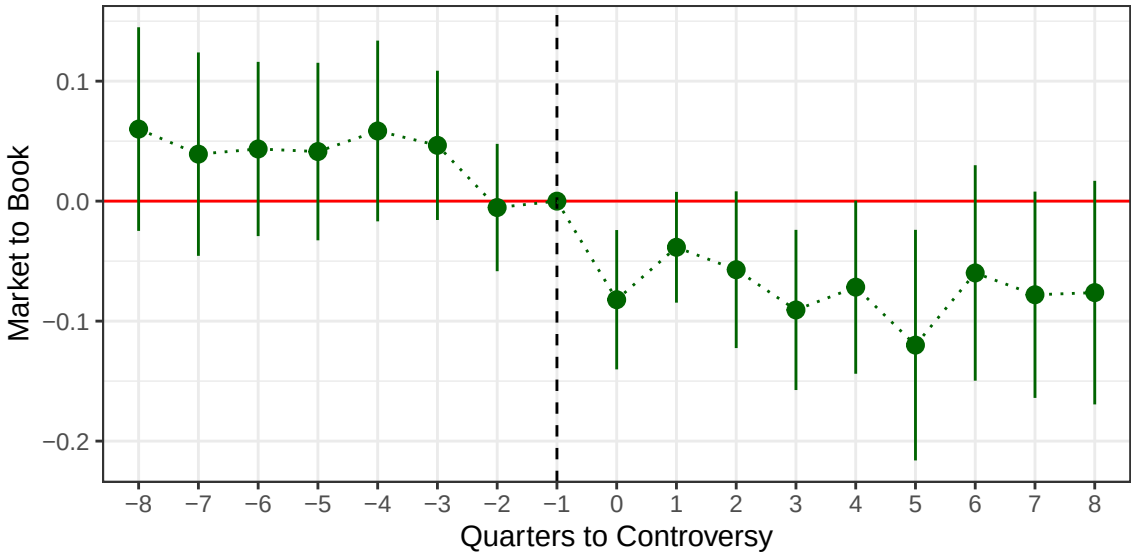
Note: This table reports estimated coefficients from model 1.11, the regression of a change in the occurrence of controversies on the hypothetical change in the share of equity owned by divestor funds due to large redemptions (*Shock to Exit*) interacted with the past (from 2010 to 2012) average Scaled CEO Wealth-Performance-Sensitivity (*WPS*, from Edmans et al. (2009), standardized for readability in Column 1), or a dummy for each quartile of the same variable (Column 2), and controls. All regressions include quarter fixed effects. Details on the construction of the variables can be found in the main text. Controversies are defined based on Ravenpack data. Stock characteristics from Refinitiv. The sample covers 1,110 US firms from 2013 to 2020. Clustered (cusip) standard-errors in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

Table 1.A14: The impact of activist cross-ownership with Seaworld on the occurrence of controversies, following the activist shareholders' revolt

Dependent Variable:	$\text{Controversy}_{n,2017Q4}$ - $\text{Controversy}_{n,2017Q2}$	
Model:	(1)	(2)
Variables		
Exposure to Seaworld	-0.427**	-0.401**
	(0.164)	(0.149)
Exposure to Seaworld × Same Industry		-0.957***
		(0.149)
Fixed-effects		
Industry × State	✓	✓
Fit statistics		
Observations	1,823	1,823
R^2	0.45048	0.45086

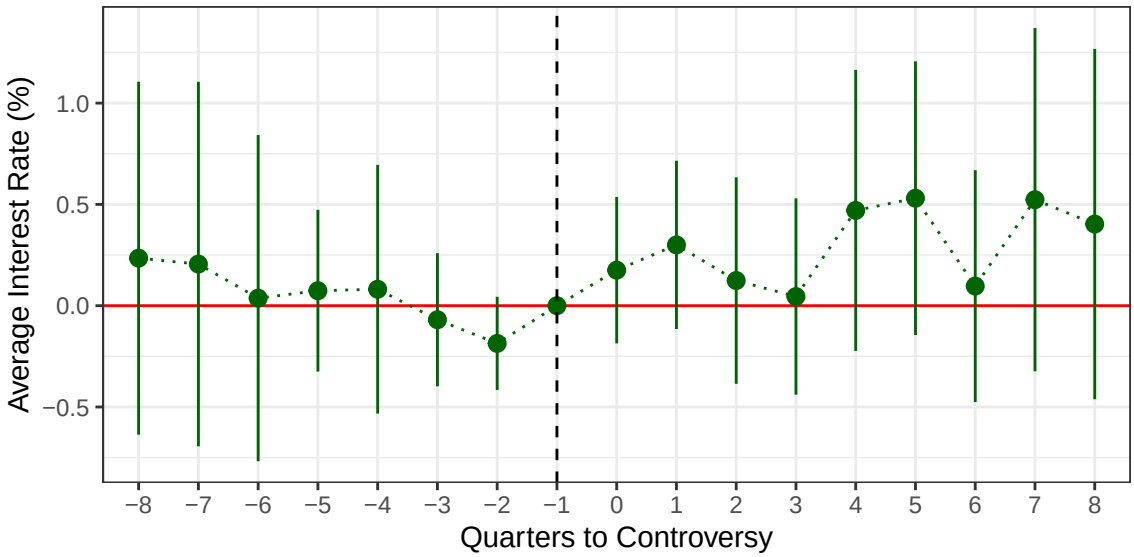
Note: This table estimates the impact of a shareholders' revolt at Seaworld in Jun 2017 on the behavior of firms in the same sector and with shared activist ownership. This table reports estimated coefficients from model 1.14, the regression of a change in the occurrence of controversies, on a measure of the common ownership between the given firm and Seaworld (*Exposure to Seaworld*), a dummy equal to one if a firm is in the same (GICS) industry as Seaworld (*Same Industry*, Column 2), the interaction between the two terms, and controls. The regression includes industry-by-state fixed effects. Details on the construction of the variables can be found in the main text. Controversies are defined based on Ravenpack data. The sample covers 1,823 US firms. Mutual fund data from CRSP. Stock characteristics from Refinitiv. Clustered (Industry) standard-errors in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

Figure 1.A1: Market to Book ratio around a controversy



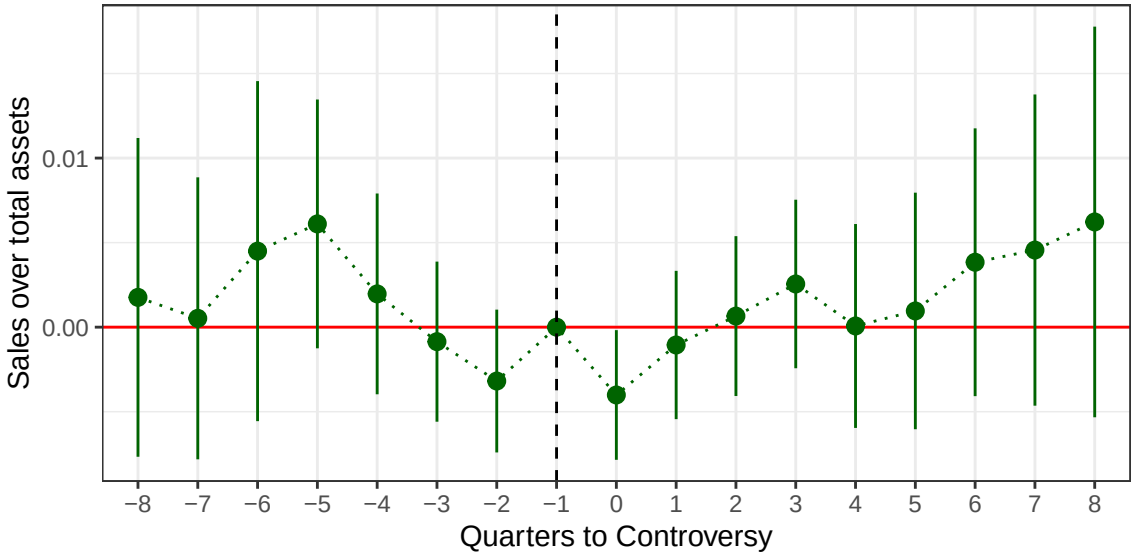
Notes: This figure displays the Market to Book ratio around the outbreak of a Social public controversy, from 2 years before to 2 years after its publication. The solid line represents the estimated coefficient, and the shaded area represents the 95% confidence interval. Accounting data from Compustat. The regression also includes firm and quarter-by-industry fixed effects. Social controversies are constructed from Ravenpack data. The sample covers 1,910 US firms from 2013 to 2020.

Figure 1.A2: Average interest rate around a controversy



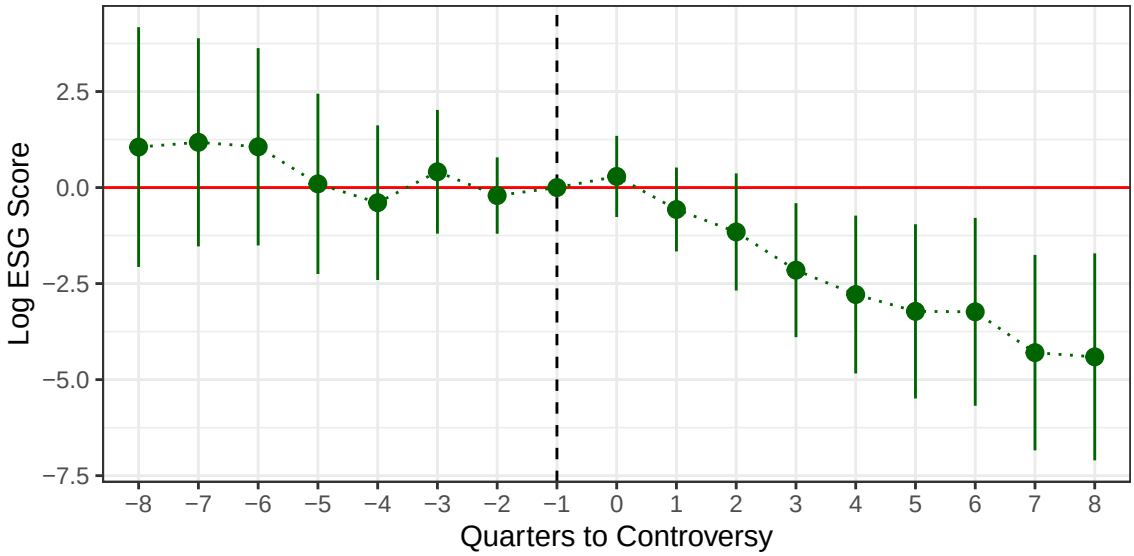
Notes: This figure displays the average interest rate around the outbreak of a Social public controversy, from 2 years before to 2 years after its publication. The average interest rate is defined as interest expenses over total debt. The solid line represents the estimated coefficient, and the shaded area represents the 95% confidence interval. The regression also includes firm and quarter-by-industry fixed effects. Social controversies are constructed from Ravenpack data. Accounting data from Compustat. The sample covers 1,910 US firms from 2013 to 2020.

Figure 1.A3: Sales over total assets around a controversy



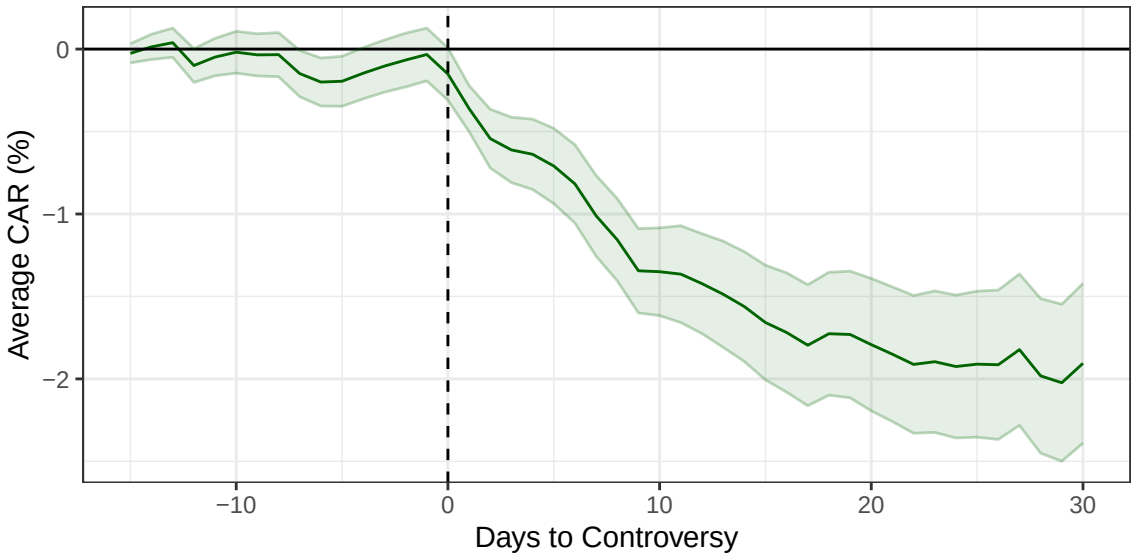
Notes: This figure displays sales over assets around the outbreak of a Social public controversy, from 2 years before to 2 years after its publication. The solid line represents the estimated coefficient, and the shaded area represents the 95% confidence interval. The regression also includes firm and quarter-by-industry fixed effects. Social controversies are constructed from Ravenpack data. Accounting data from Compustat. The sample covers 1,910 US firms from 2013 to 2020.

Figure 1.A4: Change in ESG score around a controversy



Notes: This figure displays the (logged) ESG score around a Social public controversy, from 2 years before to 2 years after its publication. The solid line represents the estimated coefficient, and the shaded area represents the 95% confidence interval. The regression also includes firm and quarter-by-industry fixed effects. Social controversies are constructed from Ravenpack data. ESG score data from Compustat. The sample covers 1,910 US firms from 2013 to 2020.

Figure 1.A5: Average CAR around a controversy - longer version



Notes: This figure displays the Cumulative Average Abnormal Returns around the outbreak of a Social public controversy, from 15 days before to 30 days after its publication. The abnormal returns are computed using a Fama and French (1993) 3-factor model. The solid line represents the estimated coefficient, and the shaded area represents the 95% confidence interval. Stock returns and betas are from CRSP. Portfolio returns and the risk-free rate are from Kenneth French's website. Social controversies are constructed from Ravenpack data. The sample covers 1,910 US firms from 2013 to 2020.

Figure 1.A6: Examples of Two N-PX Reports

(a) MassMutual Diversified Value Fund

FACEBOOK, INC. Agenda Number: 935178221

Security: 30303M102
Meeting Type: Annual
Meeting Date: 27-May-2020
Ticker: FB
ISIN: US30303M1027

Prop.#	Proposal	Proposal Type	Proposal Vote	For/Against Management
1.	DIRECTOR			
	Peggy Alford	Mgmt	Withheld	Against
	Marc L. Andreessen	Mgmt	Withheld	Against
	Andrew W. Houston	Mgmt	Withheld	Against
	Nancy Killefer	Mgmt	Withheld	Against
	Robert M. Kimmitt	Mgmt	Withheld	Against
	Sheryl K. Sandberg	Mgmt	Withheld	Against
	Peter A. Thiel	Mgmt	Withheld	Against
	Tracey T. Travis	Mgmt	Withheld	Against
	Mark Zuckerberg	Mgmt	Withheld	Against
2.	To ratify the appointment of Ernst & Young LLP as Facebook, Inc.'s independent registered public accounting firm for the fiscal year ending December 31, 2020.	Mgmt	Against	Against
3.	To approve the director compensation policy.	Mgmt	Against	Against
4.	A stockholder proposal regarding change in stockholder voting.	Shr	For	Against
5.	A stockholder proposal regarding an independent chair.	Shr	For	Against
6.	A stockholder proposal regarding majority voting for directors.	Shr	For	Against
7.	A stockholder proposal regarding political advertising.	Shr	For	Against
8.	A stockholder proposal regarding human/civil rights expert on board.	Shr	For	Against
9.	A stockholder proposal regarding report on civil and human rights risks.	Shr	For	Against
10.	A stockholder proposal regarding child exploitation.	Shr	For	Against
11.	A stockholder proposal regarding median gender/racial pay gap.	Shr	For	Against

(b) Green Century Balanced Fund

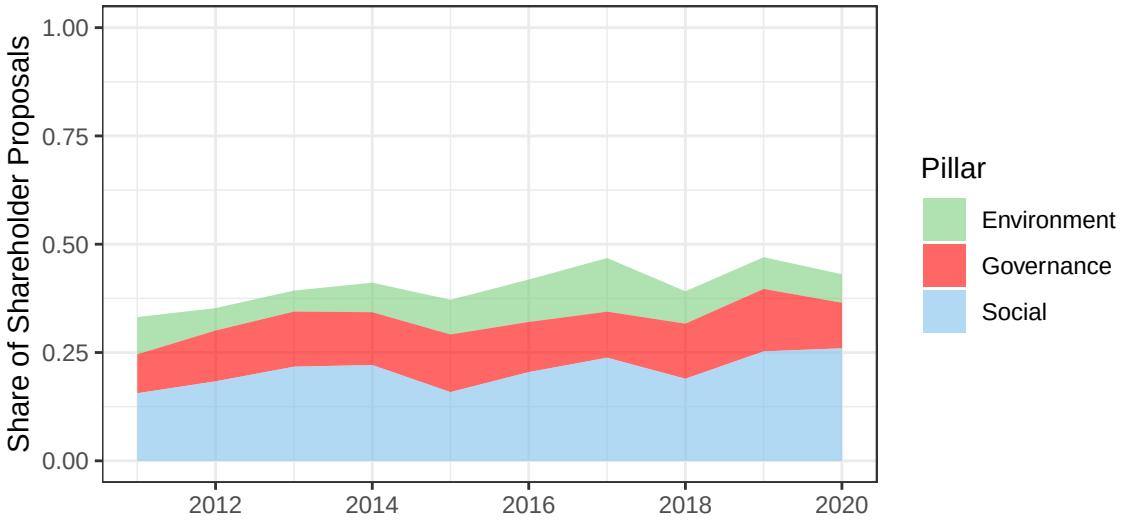
FACEBOOK, INC.

Ticker: FB Security ID: 30303M102
Meeting Date: MAY 27, 2020 Meeting Type: Annual
Record Date: APR 03, 2020

#	Proposal	Mgt Rec	Vote Cast	Sponsor
1.1	Elect Director Peggy Alford	For	For	Management
1.2	Elect Director Marc L. Andreessen	For	Withhold	Management
1.3	Elect Director Andrew W. Houston	For	For	Management
1.4	Elect Director Nancy Killefer	For	For	Management
1.5	Elect Director Robert M. Kimmitt	For	For	Management
1.6	Elect Director Sheryl K. Sandberg	For	For	Management
1.7	Elect Director Peter A. Thiel	For	For	Management
1.8	Elect Director Tracey T. Travis	For	For	Management
1.9	Elect Director Mark Zuckerberg	For	For	Management
2	Ratify Ernst & Young LLP as Auditors	For	For	Management
3	Approve Non-Employee Director Compensation Policy	For	For	Management
4	Approve Recapitalization Plan for all Stock to Have One-vote per Share	Against	For	Shareholder
5	Require Independent Board Chair	Against	Against	Shareholder
6	Require a Majority Vote for the Election of Directors	Against	Against	Shareholder
7	Report on Political Advertising	Against	Against	Shareholder
8	Require Independent Director Nominee with Human and/or Civil Rights Experience	Against	Against	Shareholder
9	Report on Civil and Human Rights Risk Assessment	Against	Against	Shareholder
10	Report on Online Child Sexual Exploitation	Against	Against	Shareholder
11	Report on Median Gender/Racial Pay Gap	Against	Against	Shareholder

Notes: The two panels show examples of N-PX reports filed at the Securities and Exchange Commission. Panel (a) is a screenshot from MassMutual Diversified Value Fund's 2020 N-PX report, with its votes at Facebook's AGM. Panel (b) is a screenshot of Green Century Balanced Fund's votes at the same AGM.

Figure 1.A7: Proportion of ESG-related shareholder proposals over time



Notes: This figure displays the proportion of ESG-related shareholder proposals among all shareholder proposals from 2011 to 2020. Data from the N-PX forms filed by mutual funds at the Securities and Exchange Commission. The classification of topics as Environmental, Social, or Governance is based on textual analysis of the reported topic of the vote. More details on the classification can be found in Appendix 1.C.

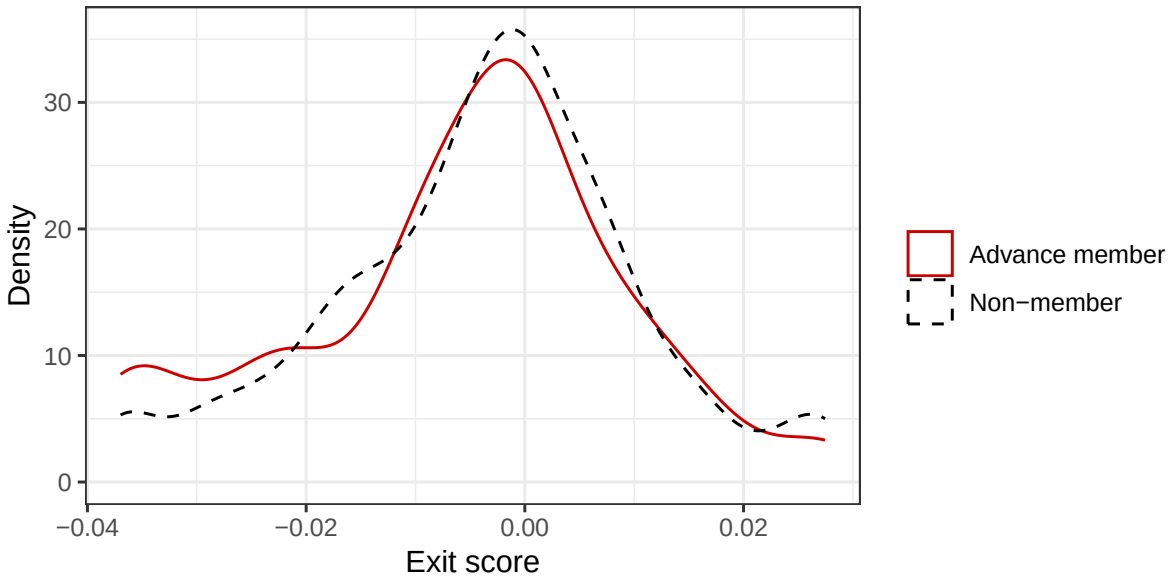
Figure 1.A8: Header of an N-PX file showing the tickers of funds covered by the form

```
<OWNER-CIK>0000877232
<SERIES-ID>S000007715
<SERIES-NAME>GREEN CENTURY EQUITY FUND
<CLASS-CONTRACT>
<CLASS-CONTRACT-ID>C000020965
<CLASS-CONTRACT-NAME>Individual Investor Class
<CLASS-CONTRACT-TICKER-SYMBOL>GCEQX
</CLASS-CONTRACT>
<CLASS-CONTRACT>
<CLASS-CONTRACT-ID>C000202490
<CLASS-CONTRACT-NAME>Institutional Class
<CLASS-CONTRACT-TICKER-SYMBOL>GCEUX
</CLASS-CONTRACT>
```

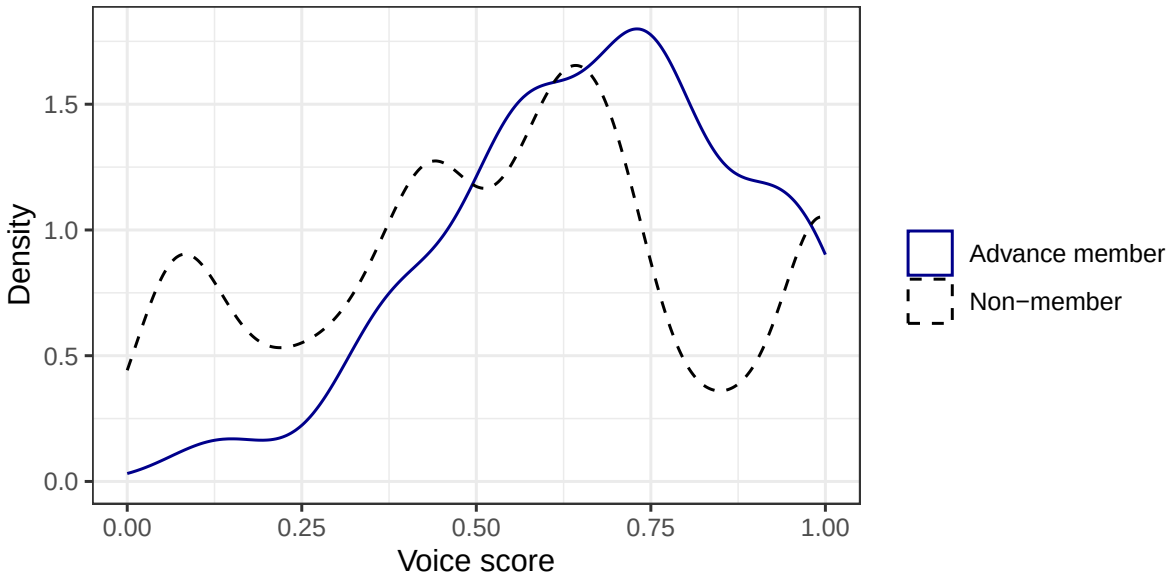
Notes: This figure is a screenshot of an N-PX form filed at the SEC by Green Century Funds. The screenshot focuses on the header of the file, showing the tickers of two of the funds covered in that specific file.

Figure 1.A9: Exit and voice by PRI's *Advance* intiative status

(a) Funds' exit score by PRI's *Advance* status



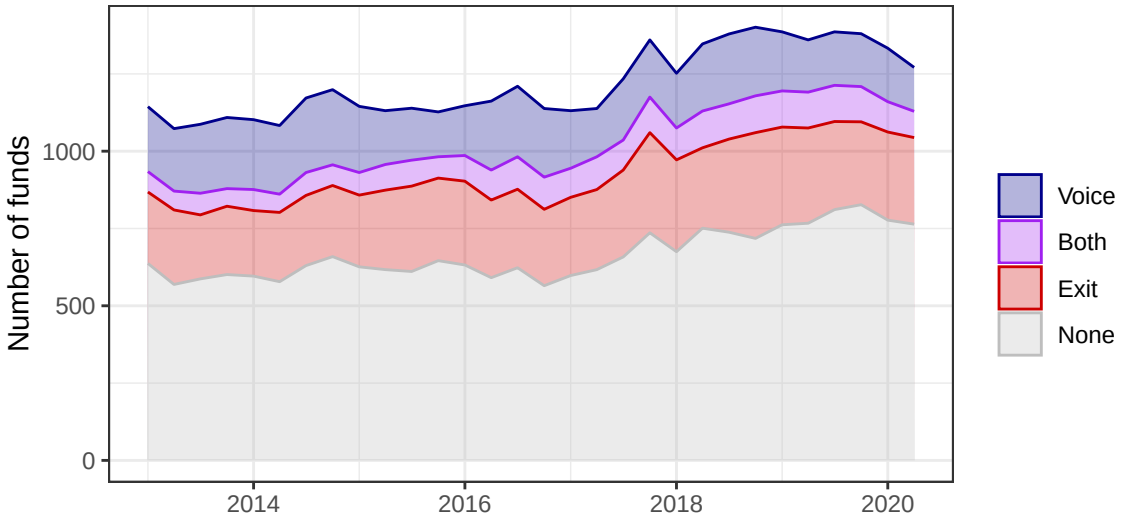
(b) Funds' voice score by PRI's *Advance* status



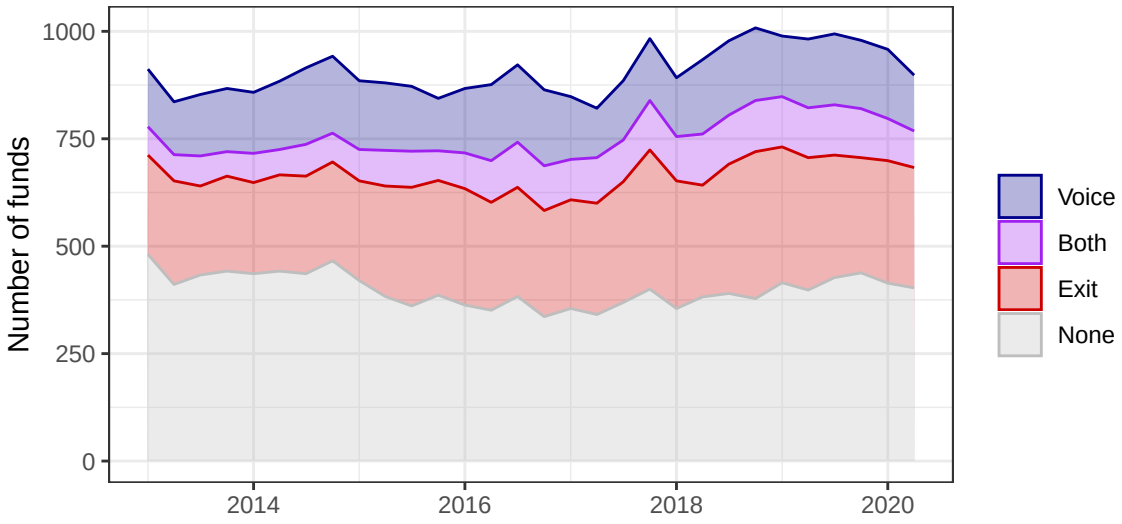
Notes: This figure displays the distribution of exit score exit (top) and voice score (bottom), depending on whether the fund is managed by a participant in the Principle for Responsible Investment's Advance initiative (solid line), or not (dashed line). Details on the calculation of the voice and exit measures can be found in the main text. PRI Advance data from the PRI's website.

Figure 1.A10: Distribution of fund types over time

(a) Sample: all funds



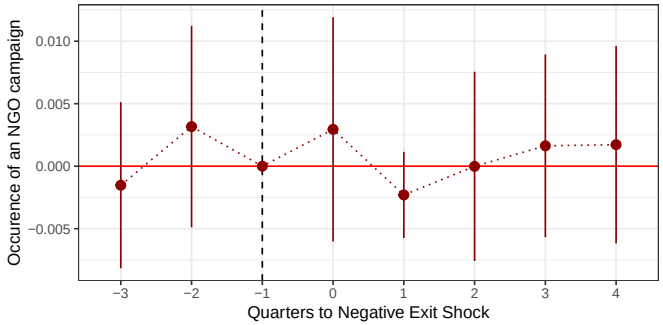
(b) Sample: excluding pure index funds



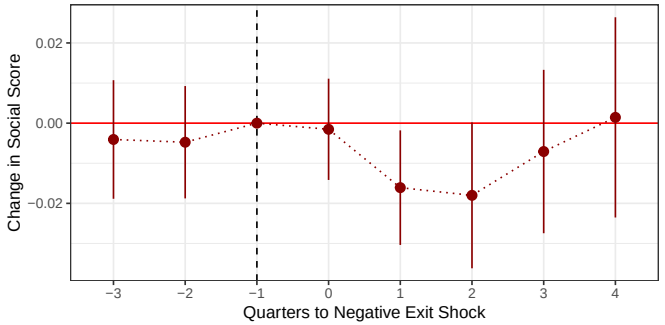
Notes: This figure displays the number of funds in each group over time, focusing on all funds in the top panel and only funds that are not identified as index funds in the bottom panel. The exit classification is based on portfolio holdings data from CRSP. The voice classification is based on voting data from the N-PX files gathered from the SEC website. Details on the construction of the exit and voice scores can be found in the main text. Based on a sample of 1,995 funds between 2013 and 2020.

Figure 1.A11: The impact of a negative shock to exit pressure on alternative CSR measures

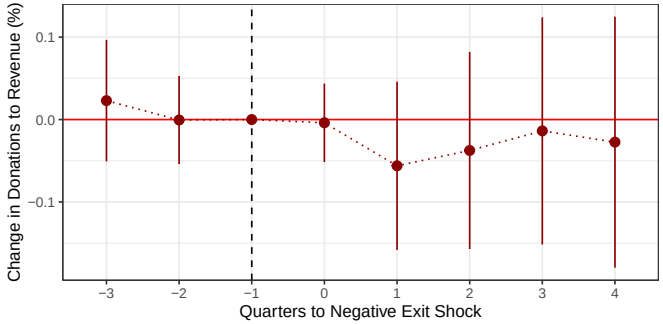
(a) Occurrence of an NGO campaign



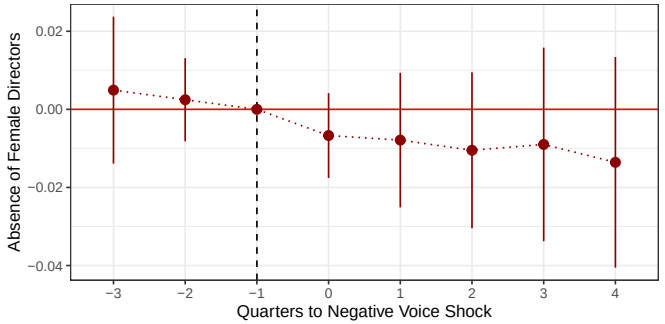
(b) Log Social score



(c) Log Donations to revenue

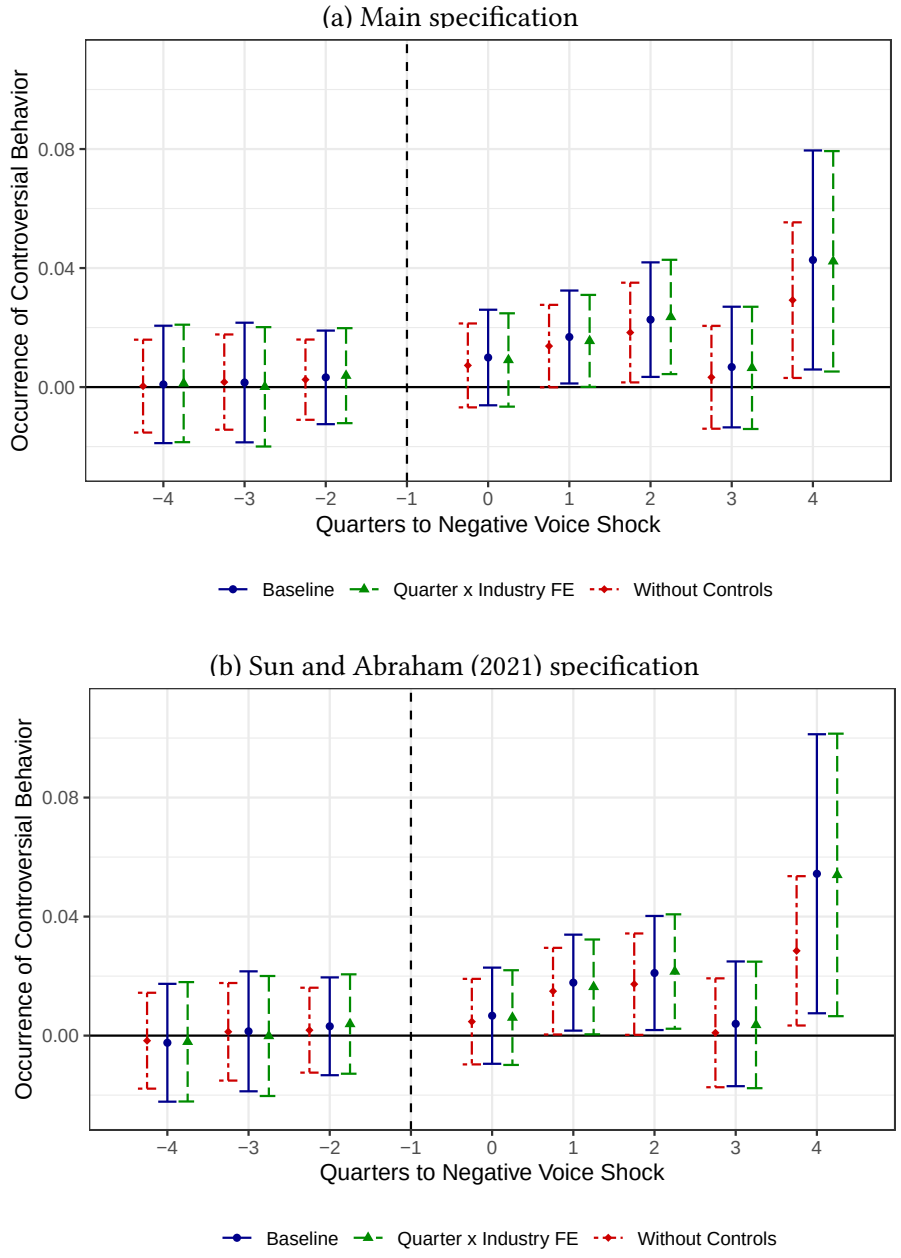


(d) Absence of female director



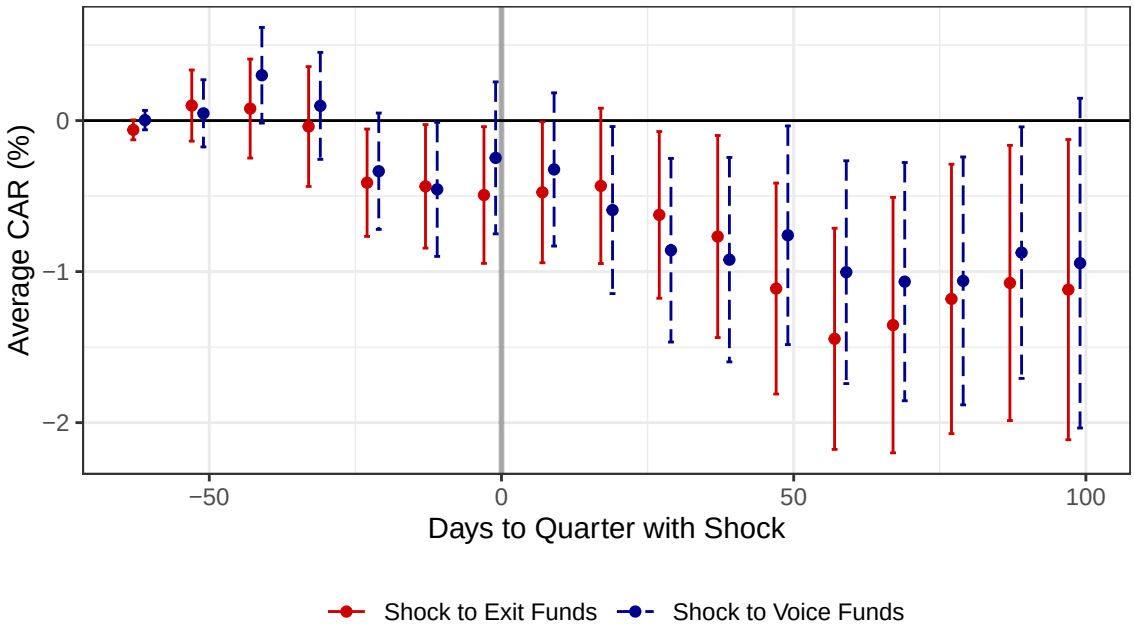
Notes: This figure displays the estimated coefficients from four event studies. The dependent variable is, alternatively, the occurrence of an NGO campaign next period (panel a), the log of the Social score (panel b), the log of donations to revenue (panel c), and a dummy indicating that there is no women on the board (panel d). Data on NGO campaigns from Koenig (2017). Data for the other dependent variables from Refinitiv. The regressions include time and firm fixed effects. The standard errors used to compute the 95% confidence interval are clustered at the firm level. An exit shock is defined as an expected change in exit due to funds' large redemptions two standard deviations away from the sample mean. The sample covers 1,910 US firms from 2013 to 2020.

Figure 1.A12: The impact of a negative shock to voice pressure on the occurrence of controversies – robustness



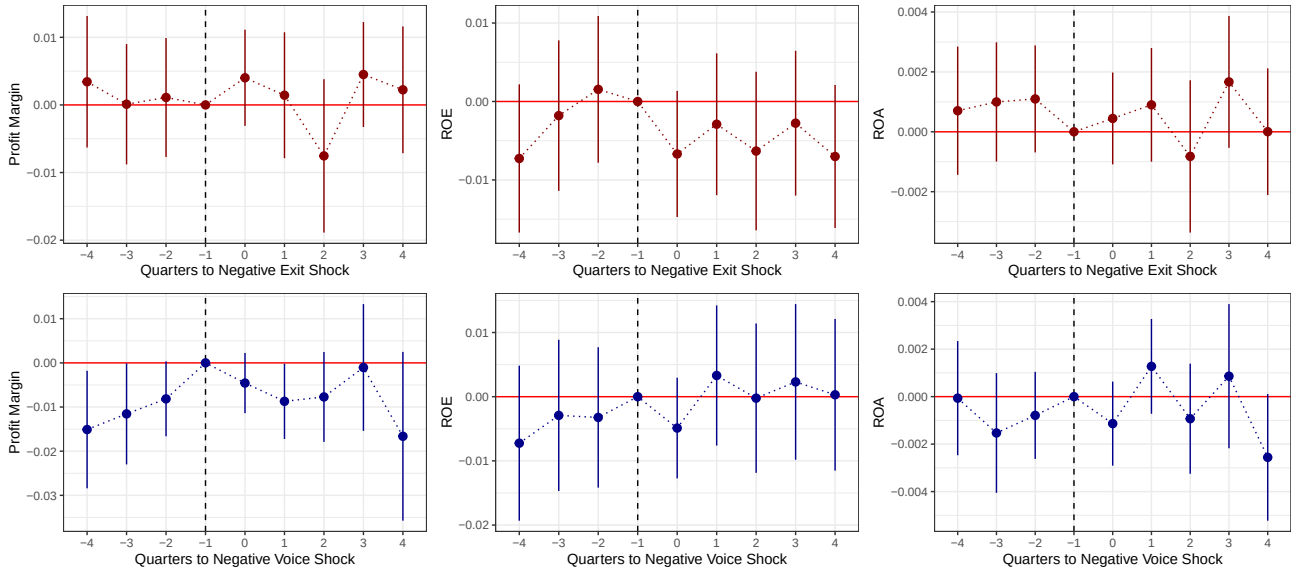
Notes: This figure displays the estimated coefficients from six event studies. The dependent variable is a dummy indicating the occurrence of a controversy the following quarter (based on Ravenpack data). Regressions in panel a) are estimated as detailed in the main text, while regressions in panel b) are estimated using the Sun and Abraham (2021) specification. The regressions include either time and firm fixed effects (baseline and without controls specifications) or firm and Quarter × Industry fixed effects. The standard errors used to compute the 95% confidence interval are clustered at the firm level. An exit shock is defined as an expected change in exit due to funds' large redemptions two standard deviations away from the sample mean. The sample covers 1,910 US firms from 2013 to 2020.

Figure 1.A13: The impact of negative shocks to exit and voice pressures on stock returns



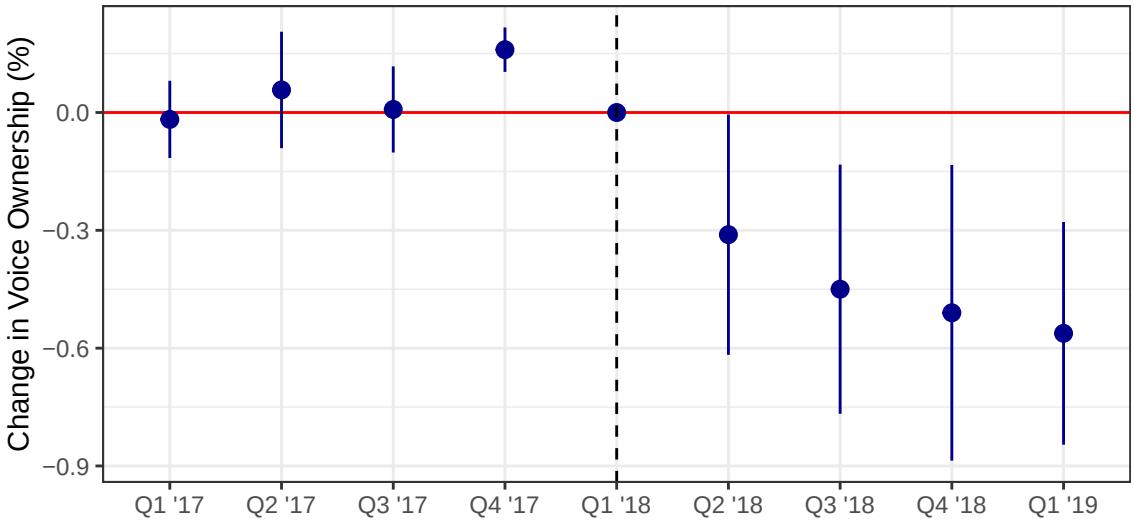
Notes: This figure displays the estimated *Cumulative Abnormal Returns* (CAR, in %), with their 95% confidence interval, of stocks hit by an exogenous decrease in exit pressure (red, solid line) or in voice pressure (blue, dashed line). The CARs are computed using a Fama and French (2015) 5-factor model, starting 63 days (a quarter) before a quarter with a shock to either exit or voice pressure. A shock is defined as an expected change in exit or voice due to funds' large redemptions two standard deviations away from the sample mean. Stock return data from CRSP.

Figure 1.A14: The impact of a negative shocks to exit and voice pressures on accounting performance



Notes: Notes: This figure displays the estimated coefficients from six event studies. The dependent variable is, alternatively, profit margin (defined as operating income over sales, first column), return on equity (income before extraordinary items over lagged book equity, second column), and return on assets (income before extraordinary items over lagged total assets, third column). All dependent variables are constructed using Compustat data and are winsorized at the 2.5 and 97.5 percentiles. The standard errors used to compute the 95% confidence interval are clustered at the firm level. An exit shock is defined as an expected change in exit due to funds' large redemptions two standard deviations away from the sample mean. The regressions alo include firm and quarter×industry fixed effects. The sample covers 1,910 US firms from 2013 to 2020.

Figure 1.A15: Exposure to Natixis-owned voice funds and voice pressure around Natixis' trading losses



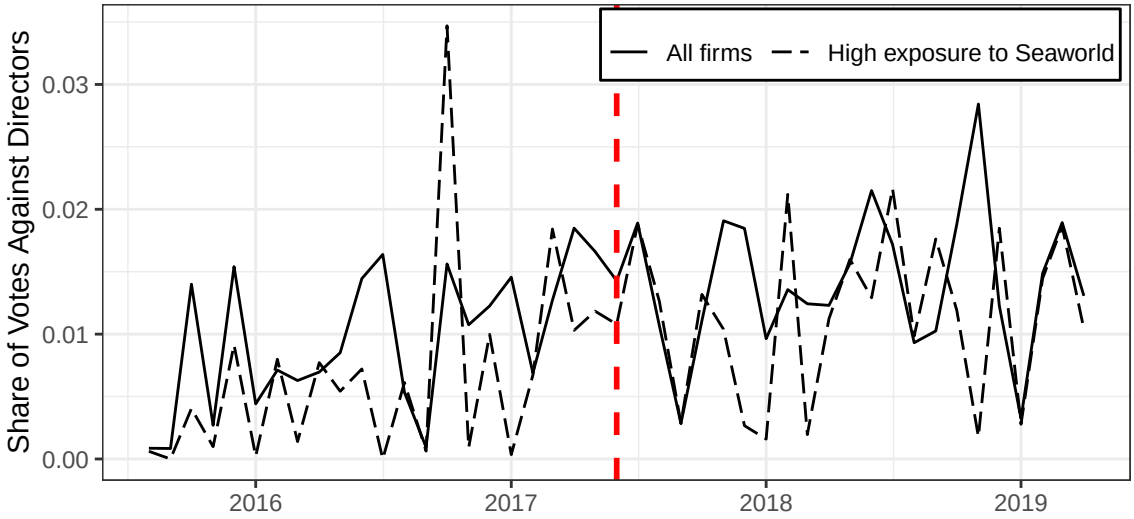
Notes: This figure displays the estimated coefficients from an event study with a firm's voice pressure as the dependent variable, and the interaction between a time dummy and the indirect exposure to Natixis through voice funds as of Q1 18 as the independent variable. The figure shows that funds with high exposure to Natixis-owned voice funds saw a decrease in their voice pressure when Natixis suffered trading losses in 2018. For instance, if Natixis owns 10% of a voice fund that owns 10% of firm n's equity, firm n's voice pressure is expected to decrease by 0.5pp after Natixis' trading losses. The regression also includes firm and quarter fixed effects. The standard-errors used to compute the 95% confidence intervals are clustered at the firm level. The sample covers 646 US firms with high indirect exposure to Natixis.

Figure 1.A16: Example of an anti-Seaworld protest after the orca's death in 2017



Notes: This figure shows a protest from the NGO Peta against Seaworld after the orca Tilikum's death in 2017. Picture taken from `https://www.seaworldofhurt.com/39-peta-orcas-simultaneously-fall-dead-los-angeles/`.

Figure 1.A17: Share of votes "against" directors, by group



Notes: This figure represents average percentage of votes against directors' elections at all firms in the sample (solid line), and at firms with above median exposure to Seaworld activists, defined as the share of equity owned by funds that are classified as voice funds and voted against the election of David F. D'Alessandro on June 14, 2017. The vertical, red dashed line represents that date. Voting data from ISS.

1.B Alternative Exit Measures

This section explores the correlation between the fund-level exit measure developed in this paper and other, potential, exit measures.

Correlation with alternative continuous measures

I consider three alternative measures of exit. First, I consider the "linear" exit, β^l_S, estimated from the linear version of equation 1.1 and excluding the zero holdings:

$$\ln\left(\frac{w_{i,t}(n)}{w_{i,t}(0)}\right) = \alpha^l_{i,t} + \beta^l_{1,i,t} \times \hat{\mathrm{m}}_{i,t}(n) + \beta^{'l}_{2,i,t} \times \mathrm{x}_t(n) + \beta^l_{S,i,t} \times \text{ Social Score}_t(n) + \ln(\epsilon_{i,t}(n)). \tag{1.B1}$$

The other continuous measure is the weighted average social score of stocks currently held by a fund:

$$SS^w_{i,t} = w_{i,t}(n) \times \sum_n \text{Social Score}_t(n).$$

The three measures are highly correlated with each other. The Pearson correlation between $\beta_{S,i,t}$ and $\beta^l_{S,i,t}$ is 0.59, with a p-value strictly less than 1%, and that between $\beta_{S,i,t}$ and $SS^w_{i,t}$ is 0.13, also statistically significant at the 1% level.

The correlation between the rankings of the funds is also positive and significant. I rank funds-quarter observation by $\beta_{S,i,t}$ decile, and compute the average $\beta^l_{S,i,t}$ decile in each group. Panel a of Figure 1.B1 shows that funds-quarter observations ranked in the $\beta_{S,i,t}$ higher deciles tend to be ranked in higher $\beta^l_{S,i,t}$ deciles. I do the same with $\beta_{S,i,t}$ deciles and $SS^w_{i,t}$ deciles in Panel b of the same figure. The same upward trend can be seen, but the difference in average $SS^w_{i,t}$ decile between the top $\beta_{S,i,t}$ deciles and the bottom ones is way smaller.

Correlation with name-based fund classification

Alternatively, I identify "S" funds based on their names. Starting from the 25,000 unique CRSP fund names, I classify as "S-labelled fund" any fund with an explicit mention of being S-oriented in its name. Those funds include KLD Social Index tracking funds, as well as funds oriented towards Womens' inclusion. I identify 62 of these funds to be explicitely S-oriented.

Those funds indeed have a much higher $\beta_{S,i,t}$ than the other funds. Their average $\beta_{S,i,t}$ is 0.2%, against an average of -0.3% for the non "S-labelled" funds. The difference between the two means is statistically significant at the 1% level. Figure 1.B2 plots the distribution of $\beta_{S,i,t}$ by group. It shows that S-labelled funds have a $\beta_{S,i,t}$ distribution shifted to the right compared to other funds.

I also check whether being an S-labelled fund predicts the preference for other financial or ESG characteristics. To that end, I run the following regressions:

$$\beta_{X,i,t} = \text{S-labelled fund} + \delta_t + u_{i,t} \tag{1.B2}$$

for the different β estimated by equation 1.1, normalized for comparability across columns. Table 1.B1 reports the results. Columns 1 to 6 show that there is no correlation between being an S-labelled fund and preferences for any financial characteristic. Columns 7 to 9 focus on the preference for stocks with high E, S, and G scores: only the coefficient on β_S is statistically significant.

Do the exit measures capture funds' exit after a controversy?

Finally, I investigate whether the three continuous measures described above capture an exit pattern among funds when a stock in their portfolio has a social controversy. I estimate equation 1.1 for index funds as well, using, for small funds, target coefficients of 1 for the β on market cap, and 0 on all other β. I then consider four different definitions of an exit fund: a positive $\beta_{S,i,t}$ and not being an index fund, a positive $\beta_{S,i,t}$ regardless of the index status (referred to as $\beta^{\text{Index}}_{S,i,t}$, a positive $\beta^{l}_{S,i,t}$ and not being an index fund, and $SS^{w}_{i,t-1} > 55$.[35]

Firm-level regression. For firms facing a controversy, I compute the share of equity owned by exit funds – defined alternatively by the above four measures the quarter before the controversy – every quarter in the year before and the year after the controversy. I run:

$$\log(\text{Ownership}_{n,t}) = \text{Post Controversy}_{n,t} + \delta_t + \gamma_n + u_{n,t}. \tag{1.B3}$$

The coefficient on $\text{Post Controversy}_{n,t}$ provides an estimate of the percentage of exit funds' ownership that is sold the year after the controversy, compared to the year before.

Table 1.B2 reports the results. For the four different measures of exit, the coefficient is negative and statistically significant at least at the 5% level. The coefficient varies from 5% to 17%. The coefficient in Column 1, where the exit status is defined as a positive $\beta_{S,i,t-1}$ and not being an index fund, is consistent with Figure 1.4. Also including index funds with a positive coefficient significantly reduces the estimate (Column 2), by one-third. Using $\beta^{l}_{S,i,t-1}$ as a reference yields a much smaller coefficient (Column 3). Finally, the coefficient estimated using exit funds defined by their weighted average social score (Column 4) yields an estimate close to the one in Column 1. For consistency, I check whether non-exit funds – as defined by the same criteria – own a smaller share of equity after a controversy (Column 5 to 8). All four coefficients are indistinguishable from zero.

[35]The choice of the 55 threshold is such that 20% of funds in the sample are exit funds, which is around the same distribution as for the other two exit measures excluding index funds.

Portfolio-level regression. I run the following regression:

$$\begin{aligned}\text{Divestment}_{i,t}(n) = \text{Controversy}_t(n) + \text{Exit}_{i,t-1} \\ + \text{Controversy}_t(n) \times \text{Exit}_{i,t-1} + \mu_{i,t} + u_{i,t}(n),\end{aligned} \tag{1.B4}$$

where $\text{Divestment}_{i,t}(n)$ is, alternatively, the arcsin transformation of the change in number of shares held, and a dummy equal to one if the change in the number of shares held is negative. $\text{Exit}_{i,t-1}$ is, alternatively, a dummy indicating that the fund i is an exit fund, according to the same criteria as above. The coefficient on the interaction term allows me to measure the extent to which exit funds decrease their exposure to stocks with a controversy more than others.

Table 1.B3 reports the result. Columns 1 to 4 report the estimated coefficients with the change in number of shares held. The coefficient on *Controversy* indicates that, in general, funds do not exit firms facing a controversy. The coefficient on the interaction term is negative and statistically significant at the 5% level when considering $\beta_{S,i,t}$: a higher exit score leads to a greater decrease in portfolio exposure to controversial stocks. When considering $\beta^{l}_{S,i,t}$ or $\beta^{\text{Index}}_{S,i,t}$, the coefficient on the interaction term decreases in magnitude, indicating that the non-linear version of the exit score excluding index funds seems to better capture the exit behavior of divestor funds. Finally, the coefficient estimated using $SS^{w}_{i,t}$ is similar to that of Column 1.

Columns 5 to 8 report the estimated coefficients with a dummy indicating a decrease in the investment in stock n. in all three columns, the coefficient on *Controversy* is positive and statistically significant: funds are more likely to reduce their investment in stocks with a controversy. Being an exit fund according to $\beta_{S,i,t}$ (Column 4) or $\beta^{\text{Index}}_{S,i,t}$ (Column 5) almost doubles that probability. The coefficient in Column 5 is smaller in magnitude and statistical significance. Finally, being an exit fund according to $SS^{w}_{i,t}$ does not lead to a higher probability of divestment.

Main result with alternative exit thresholds

Do the main results still hold when varying the exit threshold? I vary the voice score threshold from 0% to 1.5% and re-estimate model 1.7 using the new sample of voice funds. I then plot the estimated coefficient on the instrumented change in exit, as well as its 95% confidence interval, in Figure 1.B3. The plot shows that the null result on the threat of exit is robust to variations in the threshold for being an exit fund.

Selection bias in exit funds' fire sales

Finally, I investigate whether the null effect of the threat of exit can be explained by a selection bias in mutual funds' fire sales. In other words, there could be a systematic discrepancy between the actual change in exit pressure for a firm and its predicted value using mutual fund redemptions, in such a way

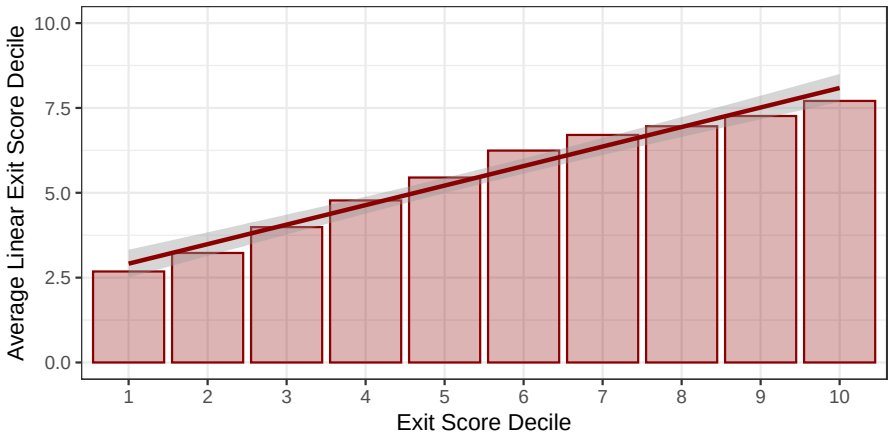
that the instrument would always be greater for certain firms, possibly more likely to face a controversy in the future. For instance, consider the case where exit funds, when facing large redemptions, sell more stocks that will face a controversy in the future: the instrument would always predict a greater (i.e., less negative) change in exit pressure than the actual change for firms with $Controversy_{n,t=2}$ =1.[36]

I test this hypothesis by regressing a dummy indicating the occurrence of a controversy in the next 2, 3, and 4 quarters on the first-stage residuals for the change in exit pressure. Results are reported in Table 1.B4, first without controls and without firm fixed effects (Columns 1 to 3, to capture the cross-sectional variation), then with firm fixed effects (Columns 4 to 6, to capture the within-firm variation), and finally with controls (Columns 7 to 10, to investigate the drivers of controversies). In all cases, the coefficient on the first-stage residuals is economically and statistically insignificant, indicating that exit funds do not sell more firms that are more likely to have a controversy in the near future. One explanation relies on the fact that a firm's Social score is a bad predictor of future controversies, as seen in Columns 7 to 10.

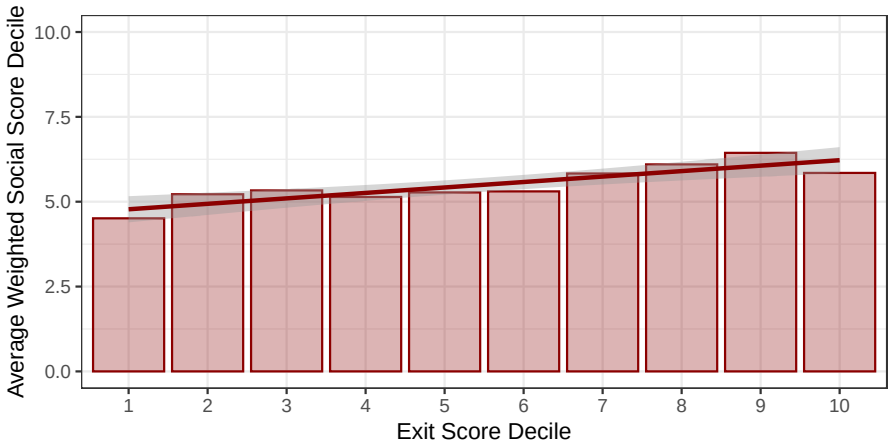
[36]Note that by the same reasoning, selling more of stocks currently facing a controversy would bias the main estimate (for $Controversy_{n,t=2}$ - $Controversy_{n,t}$) *downwards*.

Figure 1.B1: Correlation different exit measures

(a) Correlation between exit score ranking and linear exit score ranking

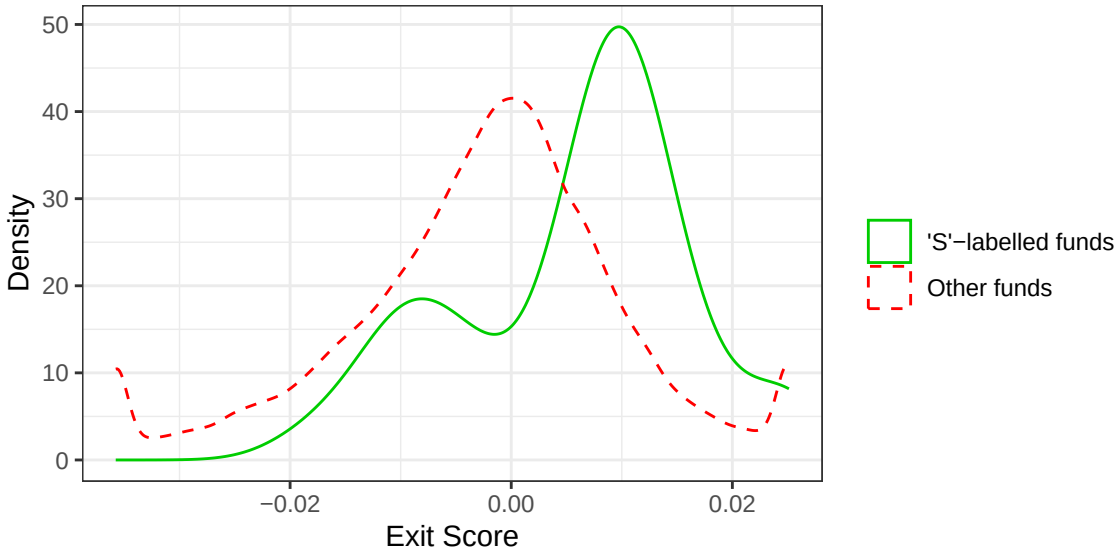


(b) Correlation between exit score ranking and weighted average social score ranking



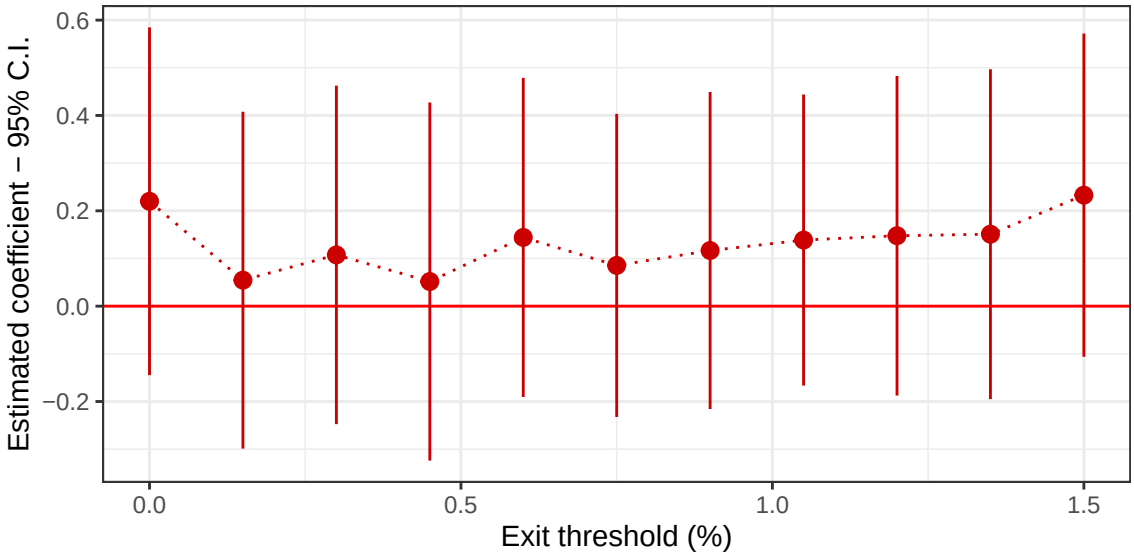
Notes: This figure displays the correlation between the ranking of funds using different measures of exit score. The x-axis is constructed by ranking funds based on their exit score as measured in the main text, and the y-axis is defined either as the average decile ranking of the same funds using their linear exit score (top) or average weighted Social Score (bottom). Fund data from CRSP. Stock data from Refinitiv. The sample covers 3,176 funds, from 2013 to 2020.

Figure 1.B2: Distribution of exit score by fund label



Notes: This figure displays the distribution of exit score for funds with an explicit pro-Social bias in their name (dark red, solid line) and other funds (black, dashed line). Fund data from CRSP.

Figure 1.B3: Estimated effect of exit on controversies, by varying the threshold for being an exit fund



Notes: This figure plots the estimated coefficients on the *Instrumented change in exit* from regression 1.7, using different definitions of an exit fund. The threshold for being a voice fund varies from 0% to 1.5%. The 95% confidence intervals are constructed from standard errors clustered at the firm level. The regressions also include: the instrumented change in voice, the change in total assets, the change in investment, the change in social score, as well as quarter fixed effects. Each regression has 37,580 observations. In all cases, the instruments pass the test for strong instruments.

Table 1.B1: S-labelled funds and portfolio allocation

Preference for:	Financial characteristics						ESG scores		
Dependent Variables:	$\beta_{\text{Market Cap}}$	$\beta_{\text{Book Eqy}}$	$\beta_{\text{Profitability}}$	$\beta_{\text{Div to Book}}$	$\beta_{\text{Investment}}$	β_{Beta}	β_{E}	β_{S}	β_{G}
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Variables									
S-labelled fund (0/1)	-0.220	0.155	-0.029	0.130	0.568	0.077	-0.032	0.650***	-0.082
	(0.372)	(0.437)	(0.210)	(0.181)	(0.360)	(0.407)	(0.267)	(0.153)	(0.181)
Fixed-effects									
Quarter	✓	✓	✓	✓	✓	✓	✓	✓	✓
Fit statistics									
Observations	69,745	69,745	69,745	69,745	69,745	69,745	69,745	69,745	69,745
R^2	0.00530	0.00471	0.00372	0.22104	0.03600	0.02619	0.00321	0.00741	0.00638

Note: This table reports estimated coefficients from model 1.B2, the regressions of funds' preference for stocks with higher market capitalization (Column 1), book equity (Column 2), profitability (Column 3), dividends to book equity (Column 4), investment (Column 5), beta (Column 6), E, S, and G scores (Columns 7 to 9), on a dummy equal to one if the fund has an explicit S-mandate in its name, and quarter fixed effects. Funds' preferences for these characteristics are estimated by Equation 1.1. All dependent variables are standardized for comparability. The sample covers 1,995 funds from 2013 to 2020. Standard errors clustered at the portfolio level are reported between parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

Table 1.B2: Different exit measures and divestment after a controversy – Firm-level regression

Dependent Variable:	Log Ownership							
Sub-sample:	Exit funds				Non-exit funds			
Exit/Non-exit status defined by:	$\beta_{S,i,t-1}$	$\beta^{\text{Index}}_{S,i,t-1}$	$\beta^{l}_{S,i,t-1}$	$SS^{w}_{i,t-1}$	$\beta_{S,i,t-1}$	$\beta^{\text{Index}}_{S,i,t-1}$	$\beta^{l}_{S,i,t-1}$	$SS^{w}_{i,t,-1}$
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables								
Post Controversy	-0.122***	-0.088***	-0.054**	-0.168***	-0.023	0.005	-0.031	-0.008
	(0.022)	(0.014)	(0.023)	(0.034)	(0.023)	(0.022)	(0.023)	(0.023)
Fixed-effects								
Quarter	✓	✓	✓	✓	✓	✓	✓	✓
Firm	✓	✓	✓	✓	✓	✓	✓	✓
Fit statistics								
Observations	11,903	12,014	11,865	11,630	13,715	13,711	13,715	13,714
R^2	0.67869	0.80733	0.65011	0.78903	0.78082	0.77605	0.78203	0.78468

Note: This table reports estimated coefficients from model 1.B3, the regressions of the log ownership of exit funds (Columns 1 to 4) or non exit funds (Columns 5 to 8), for different definitions of an exit fund, from one year before to year after a controversy, on a dummy equal to one if period t is on or after a quarter with a controversy. The exit/non exit status is defined the quarter before the controversy, and by, alternatively: $\beta_{S,i,t} > 0$ and not being an index fund (estimated from model 1.1, Columns 1 and 5), a positive $\beta_{S,i,t}$ regardless of the index status (referred to as $\beta^{\text{Index}}_{S,i,t}$, Columns 2 and 6), a positive $\beta^{l}_{S,i,t}$ and not being an index fund (estimated from model 1.B1, Columns 3 and 7), and $SS^{w}_{i,t-1} > 55$ (the average social score of stocks in the portfolio, weighted by their portfolio weight, Columns 4 and 8). The sample covers 1,995 funds from 2013 to 2020. Standard errors clustered at the firm level are reported between parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

Table 1.B3: Different exit measures and divestment after a controversy – Portfolio-level regression

Dependent Variables:	$arcsin(\Delta_t \text{Shares})$				$\mathbf{1}(\Delta_t \text{Shares} < 0) \times 100$			
Lagged exit is based on:	$\beta_{S,i,t-1}$	$\beta^{\text{Index}}_{S,i,t-1}$	$\beta^{l}_{S,i,t-1}$	$SS^{w}_{i,t-1}$	$\beta_{S,i,t-1}$	$\beta^{\text{Index}}_{S,i,t-1}$	$\beta^{l}_{S,i,t-1}$	$SS^{w}_{i,t,-1}$
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables								
Controversy	-0.013	-0.021	-0.049	0.047	1.66***	1.27***	2.02***	1.79***
	(0.019)	(0.025)	(0.039)	(0.051)	(0.109)	(0.133)	(0.235)	(0.304)
Controversy × Lagged Exit	-0.299***	-0.137***	-0.177***	-0.324***	1.31***	1.42***	0.861*	0.802*
	(0.037)	(0.034)	(0.063)	(0.062)	(0.211)	(0.179)	(0.458)	(0.414)
Fixed-effects								
Portfolio × Quarter	✓	✓	✓	✓	✓	✓	✓	✓
Fit statistics								
Observations	6,071,762	6,071,762	5,965,794	5,797,857	6,071,762	6,071,762	5,965,794	5,797,857
R^2	0.38656	0.38655	0.35483	0.39412	0.44692	0.44692	0.41587	0.44937

Note: This table reports estimated coefficients from model 1.B4, the regressions of the the arcsin transformation of the change in number of shares held (Columns 1 to 4), and a dummy equal to one if the change in the number of shares held is negative (Columns 5 to 8), on a dummy equal to one if firm n faces a controversy in quarter t, and its interaction with a lagged dummy indicating whether the fund is an exit fund, for different definitions of an exit fund. The exit/non exit status is defined the quarter before the controversy, and by, alternatively: $\beta_{S,i,t} > 0$ and not being an index fund (estimated from model 1.1, Columns 1 and 5), a positive $\beta_{S,i,t}$ regardless of the index status (referred to as $\beta^{\text{Index}}_{S,i,t}$, Columns 2 and 6), a positive $\beta^{l}_{S,i,t}$ and not being an index fund (estimated from model 1.B1, Columns 3 and 7), and $SS^{w}_{i,t-1} > 55$ (the average social score of stocks in the portfolio, weighted by their portfolio weight, Columns 4 and 8). The sample covers 1,995 funds from 2013 to 2020. Standard errors clustered at the firm level are reported between parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

Table 1.B4: Selection in exit fund fire sales, and the occurrence of controversies

Dependent Variables:	$Controversy_{n,\tau}$								
τ=	*t+2*	*t+3*	*t+4*	*t+2*	*t+3*	*t+4*	*t+2*	*t+3*	*t+4*
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Variables									
First-stage residual	-0.030	-0.054	-0.057	0.024	-0.009	-0.029	0.003	-0.041	-0.059
	(0.039)	(0.044)	(0.046)	(0.039)	(0.043)	(0.049)	(0.039)	(0.044)	(0.046)
Book-to-Market							-0.176***	-0.207***	-0.216***
							(0.061)	(0.066)	(0.066)
Log Total Assets							0.024***	0.025***	0.026***
							(0.004)	(0.004)	(0.004)
Investment							0.018**	0.016*	0.015
							(0.009)	(0.010)	(0.010)
Social Score							0.005	0.002	0.003
							(0.016)	(0.016)	(0.017)
Fixed-effects									
Quarter	✓	✓	✓	✓	✓	✓	✓	✓	✓
Firm				✓	✓	✓			
Fit statistics									
Observations	25,752	23,970	22,245	25,752	23,970	22,245	25,752	23,970	22,245
R^2	0.00139	0.00169	0.00175	0.27565	0.28357	0.28592	0.03939	0.04147	0.04199

Note: This table reports estimated coefficients from the regressions of a dummy indicating the occurrence of a controversy over different horizons, on *First-stage residual*, the difference between the actual change in exit pressure and the predicted change in exit pressure due to large redemptions, controls (in models 7 to 9), quarter fixed effects, and firm fixed effects (in models 4 to 6). Controversies are constructed using Ravenpack data. Accounting data from Refinitiv. Standard errors clustered at the firm level are reported between parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

1.C Resolutions Classification

I classify the topics of the votes reported in the form N-PX as being related to the Environment (E), Social (S), or Governance (G), based on a list of keywords. The breakdown of each category is as follows:

- The “E” category includes the following keywords: ”GHG emissions”, “GHG reduction”, “water use”, “pollution”, “climate”, “fossil fuels”, “CA100”, ”packaging”, “food waste”, “natural gas”, “environmental”, “oil”, “gas”, “Paris agreement”, “two degree scenario”, “carbon”, “pesticide”, “flaring”, “coal”, “deforestation”, “renewable”, “clean energy”, “stranded asset”, “transition risk”, “physical risk”, “nuclear”, “methane”, “protein diversification”, “energy risk”, “water stewardship”, “Bhopal”, ”green energy”,“green house”, “degree scenario”;
- The “S” category covers: : “lobbying”, “indigenous”, “pay disparity”, “political spending”, “pharmaceutical pricing”, “arbitration”, “whistle blower”, “health risk”, “discrimination”, “promotion velocity”, “human rights”, “hate speech”, “privacy risk”, “EEO”, “equal employment”, “public policy advocacy”, “sugar”, “animal test”, “child exploitation”, “fake news”, “diversity”, “inclusion”, “biased news”, “human capital”, “affirmative action”, “opioid crisis”, “animal welfare”, “animal fur”, “conflict zone”, “”female”, “decent work”, “privacy protection”, “incentive compensation”, “sexual harassment”, “internet privacy”, “content management”, “warning labels”, “data security”, “lgbt”, “prison labor”, “election spending”, “child labor”, “gay”, “animal feed”, “community”, “communities”, “political contribution”, “gender”, “charitable”, “racial”;
- The “G” category covers: “ESG”, “sustainability”, “benefit corporation”, “separate chair”, “board diversity”.

1.D Additional Details on the Voting Dataset

This section provides additional details on the voting dataset, its coverage, and its differences and similarities with commercial datasets like ISS.

Coverage

Investors. The dataset covers more than 3 million votes on shareholder proposals from 1,260 fund companies (identified by their CIK), from July 17, 2009 to June 30, 2020. 21% of the votes in the dataset are attributed to a social proposal. On average, a fund company faces at least one vote on a S-related topics at 34 meetings from firms in its portfolio in a year (the median is 22), and only 7% of the CIK times year observations face 0 vote.

Companies. I collect the CUSIP of the firm holding the meeting of interest from the N-PX files. As CUSIPs change over time, I merge the voting dataset with identifiers collected from Compustat Global. I am able to identify 12,490 meetings from 2,993 firms from 60 countries. Meetings held by US firms represent almost 60% of the sample, followed by Chinese, Canadian, and Argentinian firms. Figure 1.D1 provides a visual representation of the sample distribution across countries. This international cross-section allows me to investigate the rate of S-related shareholder proposals by country. I compute the share of meetings that have at least one S-related shareholder proposals, and plot the value in Figure 1.D2, subsetting on countries with at least 100 meetings in the sample. The Netherlands lead the way, with almost half of the meeting having an S-related shareholder proposal. Argentina, Germany, the US and Canada follow, with more than 25% of meetings with such a proposal. China and Mexico close the ranking, with close to 0% of meetings with an S proposal.

Comparison with the ISS voting dataset

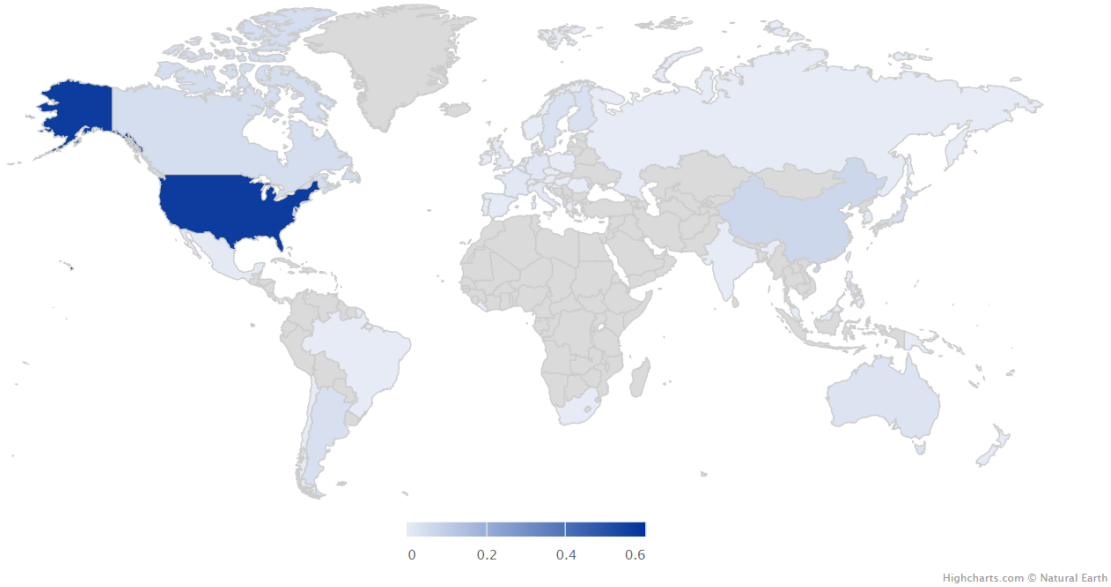
Mapping my dataset to ISS. While ISS do not report the CIK of funds that voted, they provide an *NPXFileID*, which can be recovered using the links to the N-PX files on the SEC website. As ISS uses the most recently updated CUSIP, using Compustat's company ID is crucial to further link the ISS data to mine.

Differences in coverage. From the ISS voting files, also gathered from the N-PX forms, I select all votes on shareholder proposals between 2013 and the end of 2019. The dataset covers the votes of 1,541 fund companies at 3,036 meetings from 934 firms from 17 countries.

85% of these meetings were held by firms in the US. I select only meetings that are both covered by ISS and my dataset: my dataset covers 96% of ISS' meetings, and the ISS dataset covers 23% of of the meetings in my dataset. However, ISS has 23% more voting observations, and 30% more fund companies covered.

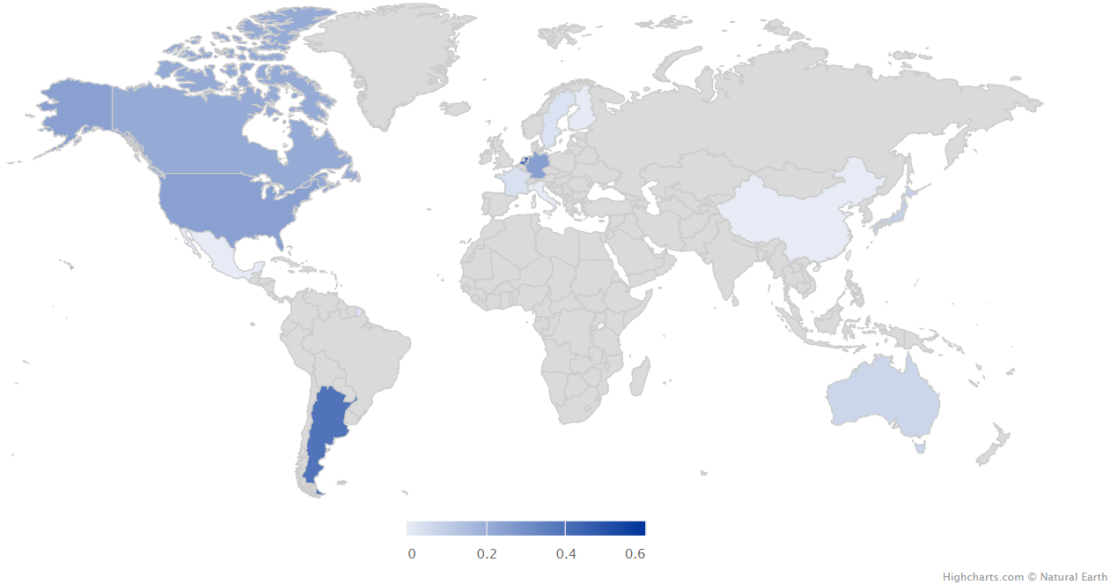
S-classification and correlation in voice measure. Focusing on meetings from US firms, I select votes on shareholder proposals for which the management recommends voting "against". In my dataset, I detect S-related proposals using the keyword detection detailed in 1.C, with around 21% of shareholder proposals being S-related. In the ISS dataset, I select proposals that are classified as "SRI" by the data provider, and exclude those with a clear environmental focus ("GHG emissions" for instance). 34% of shareholder proposals are then classified as being S-related. Then, I compute the voice score for each fund company, every quarter, using the two datasets. The coefficient of correlation is 85%, statistically significant at the 1% level. When subsetting on fund company times year observations with more than 100 observations in both datasets, the coefficient increases to 93% (p-value $<$ 1%). Using the ISS dataset leads to a similar distribution of voice scores (Figure 1.D3), although not equal. Interestingly, the distribution using ISS is more shifted to the left. Fewer funds would be considered voice funds: among the funds that would be considered here as voice with the ISS data, 95% would also be voice funds in my dataset. However, 19% of the non-voice funds with the ISS data would be considered voice with my dataset.

Figure 1.D1: Share of meetings in the dataset, by country



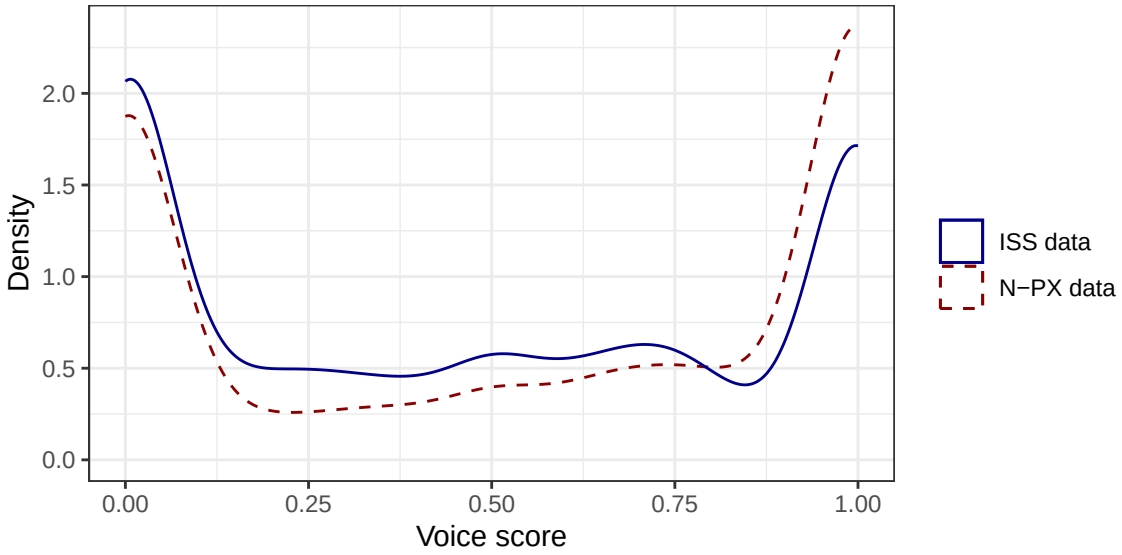
Notes: This figure displays the distribution of annual general meetings with shareholder proposals covered by the N-PX files, by country. The company's CUSIP is collected from the files and matched to a country through Compustat Global. The sample covers more than 12,000 meetings from 2009 to 2020.

Figure 1.D2: Share of meetings with S-related shareholder proposals, by country



Notes: This figure displays the distribution of annual general meetings with shareholder proposals covered by the N-PX files, by country. The company's CUSIP is collected from the files and matched to a country through Compustat Global. I detect S-related shareholder proposals using a set of keywords, detailed in Appendix 1.C. The sample covers more than 12,000 meetings from 2009 to 2020.

Figure 1.D3: Voice score distribution, by dataset used



Notes: This figure compares the distribution of voice scores computed from votes at the AGM of US firms from two different datasets: using votes on S-related shareholders proposals for which the management recommends voting against from ISS (where S-related proposals are a subset of proposals identified as ESG by the data provider), and a similar measure using the N-PX forms filed at the SEC and detecting the S-related proposals using the keywords detailed in Appendix 1.C.

1.E Funds' Portfolio Rebalancing Following Large Redemptions

This section investigates mutual funds' behavior following large investor redemptions. Its objective is to determine how long it takes for a fund to fully rebalance its portfolio following an episode of large redemptions, and so for the instrument developed in Section 1.3 to materialize in a change in exit and voice pressures. To that end, I compute quarterly net flows into funds as a percentage of their Total Net Assets (TNA). I define as a large redemption any quarterly outflow of more than 5% of a fund's TNA. Using an event-study methodology, I explore the change in some key variables following large redemptions, and the timing of the portfolio rebalancing.

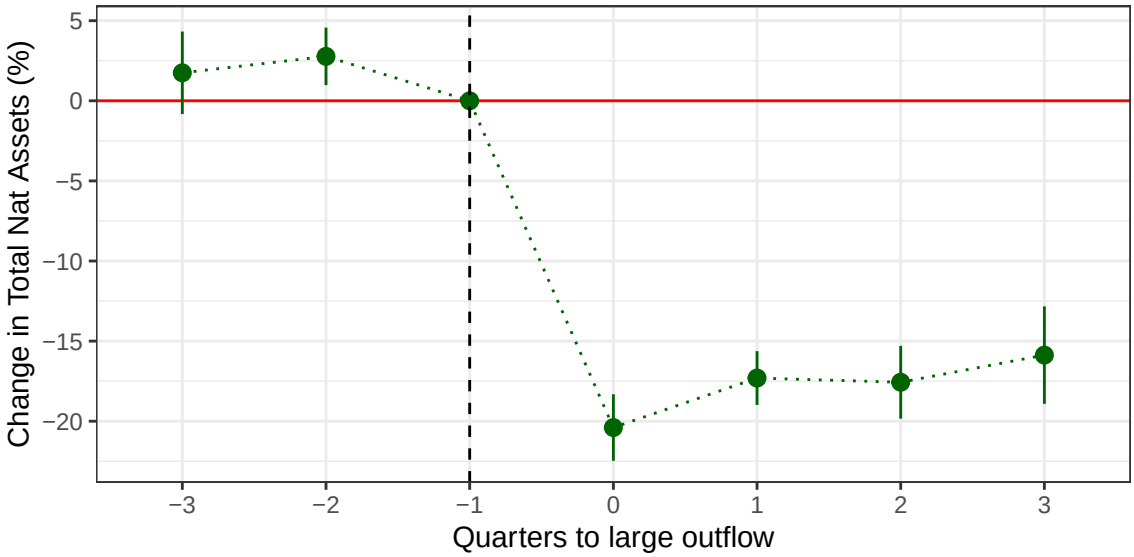
Total Net Assets. I first check that episodes of large redemptions are long-lasting and not preceded by other events of the same type. To that end, I run an event study with the log of TNA as a dependent variable, with fund and time fixed effects. The estimated coefficients are reported in Figure 1.E1. The estimated coefficients for periods -3 and -2 are indistinguishable from that on the reference period, indicating the absence of pre-trend. Then, the TNA drop in the quarter of the shock, and slowly increase in the following three quarters but remain well below their pre-shock value. We can thus conclude that large redemptions are not predicted by former large redemptions, and they do not revert quickly.

Share of equity in portfolio. Following redemptions, funds use cash in priority to minimize their price impact (Chernenko and Sunderam, 2016). Thus, changes in exit and voice due to large redemptions might not materialize in the same quarter as the shock. To empirically test that, I run an event study with the share of equity in a fund's portfolio around an episode of large redemptions. Coefficients are plotted in Figure 1.E2. Again, the estimated coefficients for the periods -3 and -2 show no pre-trend. In the quarter of the shock, the share of stocks in the fund's portfolio increases by 1.5pp, before going back to its original level the following quarter. Therefore, when facing large redemptions, funds sell relatively more non-equity assets (typically, cash or treasuries), and relatively more stocks the following quarter. In conclusion, when facing a shock at time t, funds finish their rebalancing at the end of period $t + 1$.

Number of holdings. Finally, I investigate whether funds rebalance their portfolio on the extensive or the intensive margin when they have to fire sell some of their assets. I run an event study with the number of different stocks held around a shock. The results are plotted

in Figure 1.E3: none of the coefficients is statistically distinguishable from zero.[37] That result indicates that funds prioritize an intensive margin readjustment.

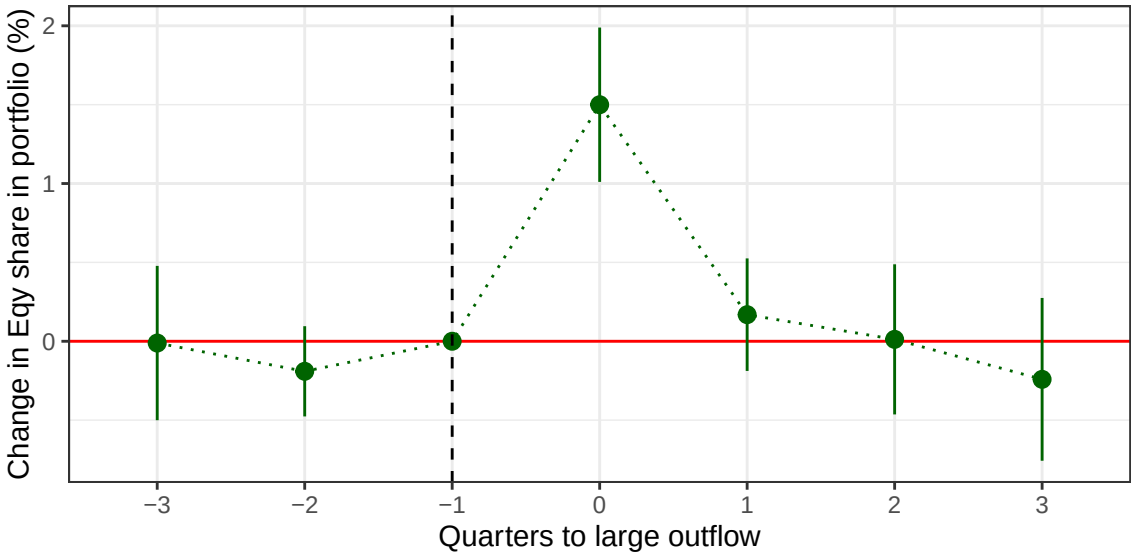
Figure 1.E1: Total Net Assets around large redemptions



Notes: This figure reports the estimated coefficients and their 95% confidence interval from an event study with a fund's Total Net Assets (logged) as the dependent variable around a quarter of large redemptions. A quarter of large redemptions is defined as any quarter during which a fund experiences an outflow of more than 5% of its TNA. The regression also includes fund and time fixed effects. Standard errors are clustered at the fund level. Data from CRSP.

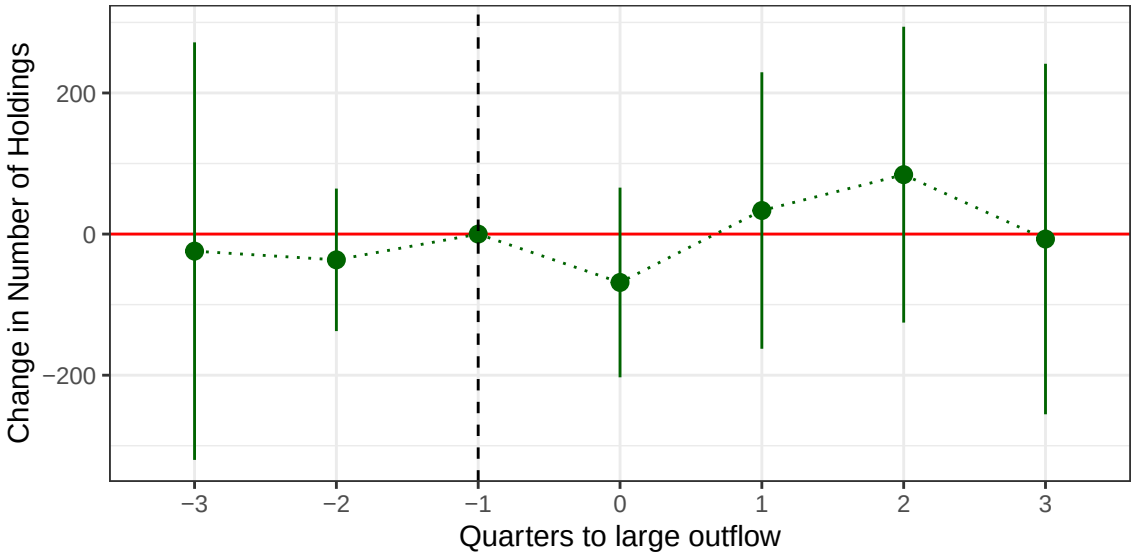
[37] Using the log of the number of different stocks held as the dependent variable does not change the result.

Figure 1.E2: Equity share in portfolio around large redemptions



Notes: This figure reports the estimated coefficients and their 95% confidence interval from an event study with a fund's portfolio share of equity as the dependent variable around a quarter of large redemptions. A quarter of large redemptions is defined as any quarter during which a fund experiences an outflow of more than 5% of its TNA. The regression also includes fund and time fixed effects. Standard errors are clustered at the fund level. Data from CRSP.

Figure 1.E3: Number of stocks held around large redemptions



Notes: This figure reports the estimated coefficients and their 95% confidence interval from an event study with a fund's number of different stocks held as the dependent variable around a quarter of large redemptions. A quarter of large redemptions is defined as any quarter during which a fund experiences an outflow of more than 5% of its TNA. The regression also includes fund and time fixed effects. Standard errors are clustered at the fund level. Data from CRSP.

1.F Alternative Voice Measures

This section explores alternative classification for voice funds, and evaluates the robustness of the main results to these alternatives.

Including shareholder proposals not opposed by the management

In the main analysis, I identify voice funds based on S-related shareholder proposals opposed by the management. This sub-section builds an alternative voice score based on all S-related shareholder proposals, regardless of the management recommendation. The main takeaway is that including these proposals changes only marginally the fund classification, as more than 83% of S-related shareholder proposals are opposed by the management. For each fund in each quarter, I compute $V_{i,t}^{\text{Against}} - V_{i,t}^{\text{All}}$, the difference between the baseline voice score and its alternative using all proposals. The difference is equal to 0 for more than 80% of the fund-quarter observations. Figure 1.F1 plots the number of observations for each value of the difference. When the difference is not equal to 0, it is positive 99% of the time, indicating that the baseline voice score overestimates the voice dimension of funds. The results are thus to be regarded as a lower bound of the effect of voice on CSR efforts.

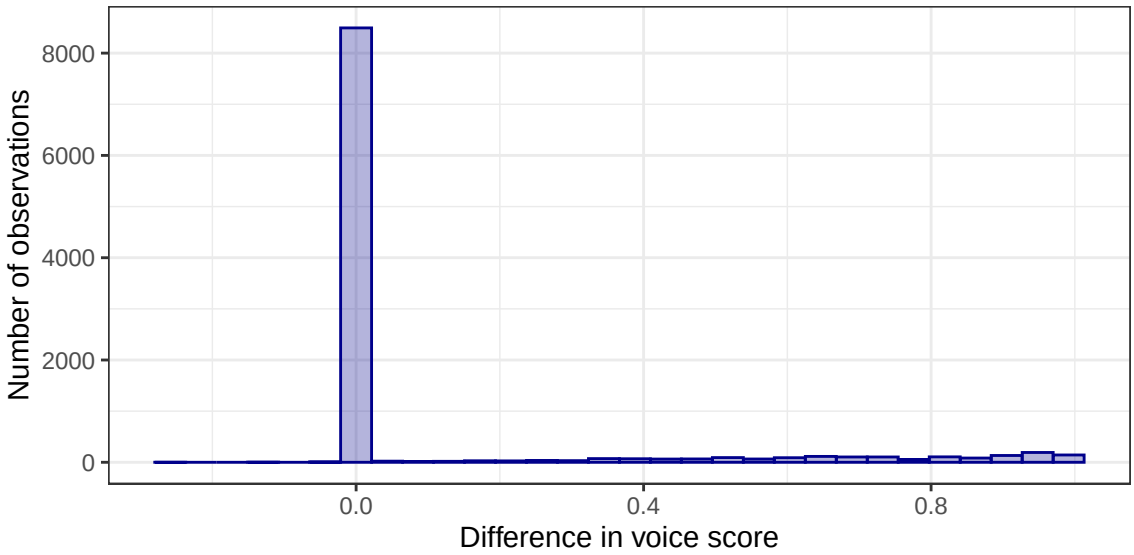
Alternative voice thresholds

Choice of the baseline threshold. The voice fund classification aims to capture funds that: *i)* vote generally in favor of S-related shareholder proposals for which the management recommends voting against (voice score $> 50\%$, and *ii)* are active voters. Being an active voter means that the classification should exclude funds that "blindly" follow proxy advisors' recommendations. Using ISS data, I estimate that ISS recommends voting in favor of such proposals between 68 and 81% of the time, depending on the quarter and the set of firms chosen (only US firms, or not). Glass-Lewis is meant to be "less pro-social" than ISS (Bolton et al., 2020). As the two combined covers more than 90% of the proxy advisory market, I expect a large number of voice scores to cluster around the proxy advisors' score. Figure 1.F2 shows the number of funds-by-quarter observations for each voice score value, from 50% to 99%. As expected, the distribution peaks at ISS' average "for" recommendation, around 72%. One can also detect a drop in the distribution around a voice score of 83%. The 85% voice score threshold is thus chosen to select funds that seem to be above the cluster of funds that follow proxy advisors most of the time.

Main result with alternative voice thresholds. Do the main results still hold when varying

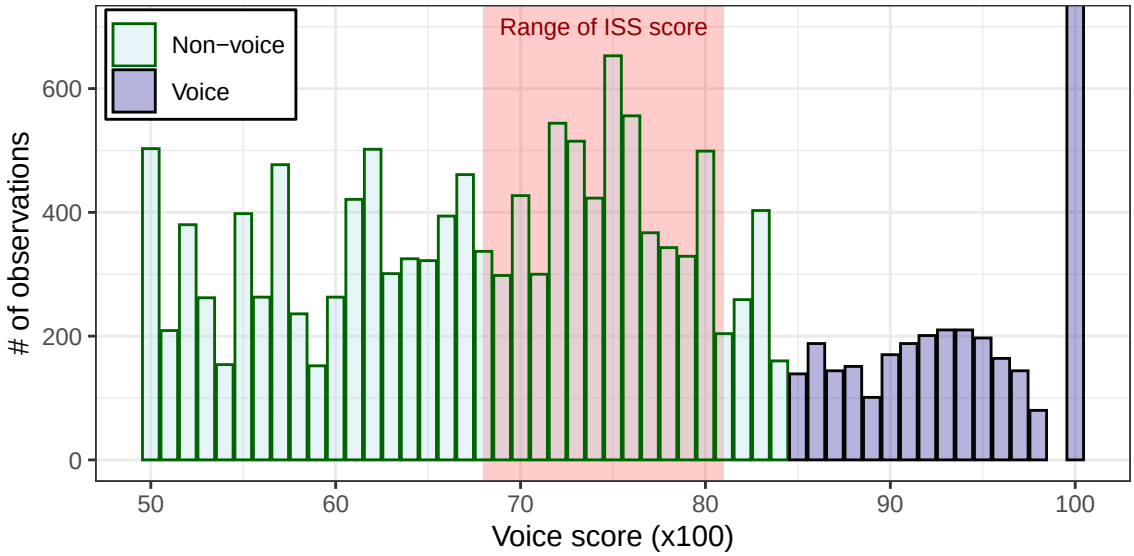
the 85% threshold? I vary the voice score threshold from 50% to 95% and re-estimate model 1.7 using the new sample of voice funds. I then plot the estimated coefficient on the instrumented change in voice, as well as its 95% confidence interval, in Figure 1.F3. The plot shows that when the threshold is set at 50%, the coefficient on the instrumented change in voice is -0.5 and its p-value is 18%. As the threshold increases, the coefficient becomes more negative and increases in statistical significance. The coefficient becomes statistically significant at the 10% level when the threshold is 65% and at the 5% level above the 75% threshold. When the threshold is set at 95%, the estimated coefficient is below -1.5. These results indicate that the improvement in CSR is due to funds with the highest voice score. It also shows the robustness of the main results: as long as the threshold is set above ISS' average recommendation, the estimated coefficient is statistically significant at the 5% level.

Figure 1.F1: Difference in voice score depending on whether shareholder proposals not opposed by the management are excluded



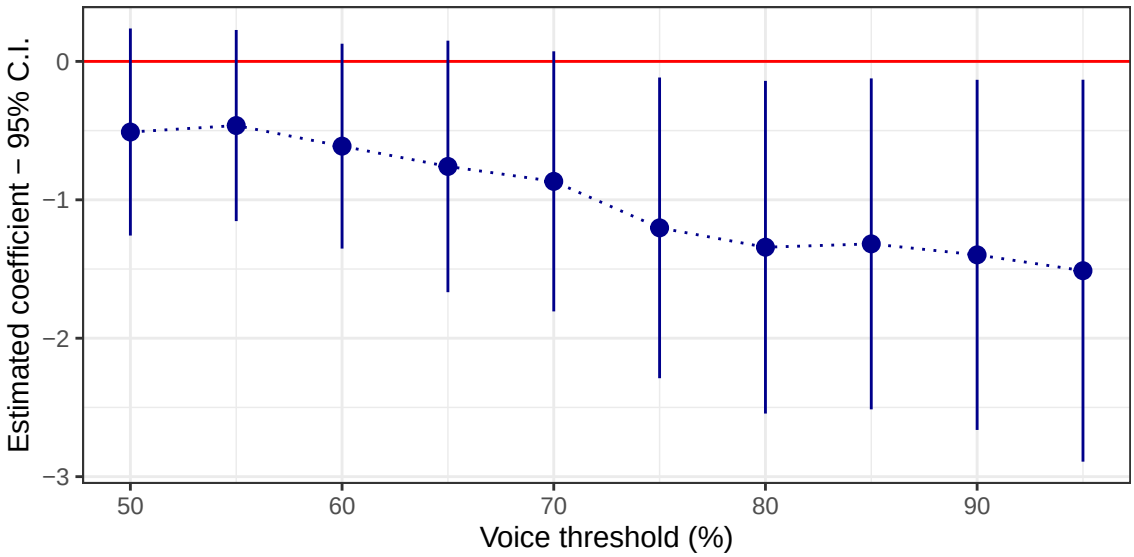
Notes: This figure plots the distribution of the difference between the baseline voice score and an alternative where the S-related shareholder proposals not opposed by the management are not excluded. The sample consists of 10,235 fund company × quarter observations, for 347 fund companies between 2010 and 2020.

Figure 1.F2: Distribution of funds-by-quarters observations by voice score



Notes: This figure shows the number of funds-by-quarter observations by voice score in the dataset. The lightblue bars show the distribution of funds that are not classified as voice funds, and the dark blue bars show the distribution of funds that are classified as voice funds. The red shaded area shows the range of ISS' "for" recommendations between 2013 and 2020. ISS recommendations data are from ISS. Funds' voice score are calculated from their votes on S-related shareholder proposals for which the management recommends voting "against", gathered from the N-PX forms filed at the SEC. The sample covers 1,995 funds from 2013 to 2020.

Figure 1.F3: Estimated effect of voice on controversies, by varying the threshold for being a voice fund



Notes: This figure plots the estimated coefficients on the *Instrumented change in voice* from regression 1.7, using different definitions of a voice fund. The threshold for being a voice fund varies from 50% to 95%. The 95% confidence intervals are constructed from standard errors clustered at the firm level. The regressions also include: the instrumented change in exit, the change in total assets, the change in investment, the change in social score, as well as quarter fixed effects. Each regression has 37,580 observations. In all cases, the instruments pass the test for strong instruments.

1.G Cost of Capital and Threat of Exit

This section investigates whether firms with a higher cost of capital respond more to the threat of exit.

Cost of capital calculations

Starting from the Weighted Average Cost of Capital (WACC) calculation:

$$\text{WACC}_{n,t} = C_{E,n,t} \times (1 - \text{Leverage}_{n,t}) + C_{D,n,t} \times (1 - \tau_{n,t}) \times \text{Leverage}_{n,t}, \tag{1.G1}$$

where $C_{E,n,t}$ is a firm's cost of equity, $\text{Leverage}_{n,t}$ is total debt over total debt and total equity, $C_{D,n,t}$ is the cost of debt, and $\tau_{n,t}$ is the tax rate. While the calculation of the cost of debt has found a (relative) consensus as interest expenses over debt, the calculation of the cost of equity is subject to intense debate. Despite its numerous shortcomings (see, for instance, Fama and French, 1996, Krüger et al., 2015), the use of the CAPM remains widespread. Following Frank and Shen (2016), I consider three definitions of the cost of debt: one CAPM-based, one based on the Fama-French 3-factor model, and one based on a one-period Gordon growth model. Alternatively, and to highlight the role of debt, I consider firms' S&P long-term rating.

Results

I run the main specification on sub-samples of the dataset based on previous period's measure of cost of capital. For the three WACC measures, I divide the sample between above and below median WACC. For the S&P long-term rating, I divide the sample between firms with a speculative grade rating, and firms with an investment-grade rating. Results are reported in Table 1.G1. In Columns 1, 3, 5, and 7, focusing on firms with a plausibly higher cost of capital, the coefficient on the instrumented change in exit is negative only once, but not statistically significant. It is even positive and weakly significant when considering firms with low credit rating. On the contrary, the coefficients in Columns 2, 4, 6, and 8 are positive 3 times out of four, and weakly significant in the case of high credit rating. Thus, I do not find evidence that a higher cost of capital leads to be more prone to listen to exit shareholders.

Table 1.G1: Threat of exit at firms with high cost of capital

Dependent Variable:	$\text{Controversy}_{n,t+2}$-$\text{Controversy}_{n,t}$							
Cost of capital measure:	WACC based on						Long-term credit rating	
	CAPM		FF3		GMM		S&P Rating	
Sub-sample	Above median	Below median	Above median	Below median	Above median	Below median	Junk rating	IG rating
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables								
Instrumented Change in Exit	-0.437	0.306	0.210	-0.211	0.024	-0.061	0.807*	-1.93*
	(0.453)	(0.401)	(0.331)	(0.500)	(0.393)	(0.454)	(0.419)	(1.15)
Change in Total Assets	-0.001	-0.003	0.013	-0.014	0.013	-0.011	-0.001	-0.028
	(0.021)	(0.022)	(0.016)	(0.024)	(0.019)	(0.020)	(0.019)	(0.050)
Change in Investment	0.003	-0.005	-0.005	0.0009	0.006	-0.003	0.015	0.008
	(0.018)	(0.018)	(0.017)	(0.019)	(0.024)	(0.015)	(0.021)	(0.037)
Change in Social Score	-0.084	-0.598	-0.096	-0.493	-0.087	-0.739	-0.035	0.075
	(0.089)	(0.412)	(0.111)	(0.341)	(0.100)	(0.497)	(0.030)	(0.059)
Fixed-effects								
Quarter	✓	✓	✓	✓	✓	✓	✓	✓
Fit statistics								
Observations	22,563	22,295	22,738	22,120	23,067	21,788	13,094	18,298
Effective F-statistic	250.60	122.66	136.18	152.76	207.94	133.55	71.471	89.161

Note: This table reports estimated coefficients from model 1.10, This table reports estimated coefficients from the regression of a change in the occurrence of controversies on the change in the share of equity owned by exit funds instrumented by the hypothetical change in that share due to large redemptions (*Instrumented Change in Exit*), for different sub-samples. The sub-samples are based on being above or below the (lagged) median cost of capital, for different measures of a firm's cost of capital. Columns 1 to 6 are based on a Weighted Average Cost of Capital (WACC, from Model 1.G1), and on the S&P long-term credit rating in Columns 7 and 8. The WACC is, alternatively, computed using a cost of equity based on: the CAPM (Columns 1 and 2), the Fama and French (1993) 3-factor model (Columns 3 and 4), and the Gordon Growth Model (Columns 5 and 6). Standard errors clustered at the firm level are reported between parentheses. *Change in Social Score* is divided by 100 for readability. The *Effective F-statistic* is the Olea and Pflueger (2013) first-stage F-statistic. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

Chapter 2

The Shared Cost of Pursuing Shareholder Value*

Co-authored with Michele Fioretti and Simon C. Smith

Abstract

We propose a portable framework to infer shareholders' preferences and influences on firms' prosocial decisions and the costs these decisions impose on firms and shareholders. Using quasi-experimental variations from the media coverage of firms' annual general meetings, we find that shareholders support costly prosocial decisions, such as covid-related donations and private sanctions on Russia, if they can earn image gains from them. In contrast, shareholders that the public cannot readily associate with specific firms, like financial corporations with large portfolios, oppose them. These prosocial expenditures crowd out investments at exposed firms, reducing productivity and earnings by between 1 and 3%: pursuing the values of some shareholders comes at the cost of others, which the shareholders' monitoring motivated by heterogeneous preferences could prevent.

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"[...] it is the job of the manager of a firm [...] not only to [...] organize production, but also to learn about the *preferences* of the firm's shareholders."

Grossman and Hart (1979)

2.1 Introduction

Shareholder disagreements are common but often unobserved. As shareholders try to influence managers, policies have been implemented to inform shareholders (e.g., Desai et al., 2007) and resolve conflicts by allowing them to make proposals and vote at the Annual General Meetings (AGMs) of shareholders (e.g., DeMarzo, 1993, Bouton et al., 2022). However, some shareholders can also influence managers through private channels, reducing the ability of non-connected shareholders to access managers and limiting managerial knowledge regarding shareholder preferences over firms' decisions. Social responsibility adds another dimension to shareholder conflicts because shareholders may disagree not only on the profitability of firms' actions, but also on their social implications (Landier et al., 2009, Fioretti, 2022). Consider Ford Motor's decision to convert some of its car production facilities to produce and donate medical ventilators to hospitals during the pandemic when ventilators, essential to treating patients with COVID-19, were in shortage. Due to its costs, shareholders might hold different views about the firm's decision. Those who derive "value" from covid relief may have supported it despite smaller financial returns as their cash donations could not help hospitals procure ventilators (Hart and Zingales, 2017). Shareholders easily associated with Ford Motor could benefit further from the media coverage of the firm's generosity, as is the case of Bill Ford, a member of the Ford family who, when interviewed by CBS, endorsed the donation of ventilators.[1] On the other hand, for shareholders such as US households who do not benefit from similar private returns, donations resemble taxes (Friedman, 1970). These differences in preferences raise questions about the consequences of pursuing the values of some shareholders at the cost of others.

Our main contribution is to empirically investigate the shared costs of shareholders' influence by drawing a causal link between their preferences and the prosocial decisions of large global corporations. To overcome the main issue that we face, namely that shareholder influence is not observable, we focus on settings where a sudden emergency puts firms in an

[1] "[...] When we look at this crisis– as a country and said, you know, which industry is positioned to help us not only in terms of sophisticated machinery, but can do a lotta them and a lotta them quickly, the auto industry is uniquely positioned to do that" (O'Donnell, 2020). This example is illustrative as ventilator productions were economically supported by the Defense Production Act (i.e., government contracts), while this paper focuses only on voluntary donations.

advantageous position to procure society with needed goods and services compared to what shareholders can achieve through cash donations. Exploiting the exogenous occurrence of AGMs as a shock to corporate news coverage, we find that the shareholders most likely to gain image returns from their firm's prosocial decisions demand positive changes. In contrast, shareholders with limited opportunities to extract private gains see these demands as externalities and oppose them because the associated costs can reduce a firm's profits and growth prospects. As a result, market capitalization and operating income drop by about one to three percentage points more at the firms most exposed to these externalities, resulting in adverse outcomes for "silent" and "unheard" shareholders. These losses come from inefficient expenses cutting current funds that would otherwise have been invested, describing a feedback loop curtailing future productivity.

Motivated by a stylized theoretical model of a contest where shareholders with different preferences about a corporate prosocial action compete to influence managers (e.g., Konrad et al., 2009), we expect that, net of prosocial inclinations, shareholders with significant shares in the firm and no private returns from its prosocial decision oppose the action if it reduces the firm's profits. On the contrary, shareholders who can gain private returns from the prosocial action will support it if these returns exceed their losses. Also inspired by the common ownership literature (e.g., Azar et al., 2018, Backus et al., 2021), we identify the former shareholders in institutional investors – financial intermediaries such as mutual funds and banks – whom the public hardly connects with a specific firm as they own shares across many firms, and the latter shareholders in individual and family shareholders, who are synonymous with a firm.Importantly, some of these shareholders can be past or current managers without affecting our results, as discussed below.

Our empirical framework relies on a sudden emergency where the public demands firms to take costly prosocial actions and on the exogenous variation of AGM timing across firms, which we show to heighten a firm's media coverage, thereby increasing the media attention of its most recognizable shareholders.[2] The International Shareholder Services (ISS), a global leader in proxy voting services, requires firms to allow 90 days between the date when shareholders receive materials about the AGM proposals and the AGM. Consider the recent pandemic as a similar emergency. The first reported US covid case occurred on January 15, 2020 (Holshue et al., 2020): since the firms with AGMs planned for the following 90 days could not move their dates by law (SEA, 1934), the increased media attention due to the AGM period is independent of the preferences of shareholders and managers toward the donations, the composition of the shareholding body and their access to managers, and the financial and operational status of a

[2]We verify empirically that a firm's media coverage increases during its AGM period (Appendix 2.C).

firm. These features make our approach portable across crises (or even countries) and times.

Therefore, we estimate the impact of shareholder preferences on corporate decisions as the difference in the donation rates observed by April 15, 2020, across four groups of firms: *i)* the difference across treated firms (i.e., with an AGM before 90 days from the beginning of the crisis) with and without large individual (or institutional) shareholders and *ii)* the same difference across control firms (i.e., with no plans for an AGM in this period). Since firms donated covid-relief cash and goods like facemasks, sanitizing gels, and software, we focus on explaining why firms donated rather than the value of the donations. At S&P 500 firms, cash donations averaged 1% of EBIT alone, a substantial cost for a firm's shareholders but great publicity for the most visible ones.

We find that by April 15, treated S&P 500 firms are 9% more likely to donate to covid-relief if their shareholding body includes large individual shareholders before the pandemic compared to the average S&P 500 firm. In contrast, treated firms with large institutional shareholders are 15% less likely to donate compared to the average S&P 500 firm. Consumer demand for covid-related donations, managerial will, peer pressure from donating competitors, and financial returns do not explain our findings.

We validate the image-gain mechanism showing an instantaneous and sustained gap in the Google searches of the names of a firm's individual shareholders compared to those of its institutional shareholders around the donation news date; this gap widens by about 40% in each of the ten days following a donation. Nonetheless, institutional shareholders are not necessarily against covid-related donations: several S&P 500 financial firms donated directly, but their donations negatively correlate with those of the S&P 500 firms in their portfolios. Thus, shareholders support donations only if their influence yields direct private benefits, creating an externality on other shareholders. These returns can be micro-founded as warm glow utilities (e.g., Andreoni, 1989) or reputational gains from virtue signaling (e.g., Bar-Isaac et al., 2008).

We demonstrate the portability of our framework in two ways. First, we study another focal event of the last decade, namely the decision of US multinationals to forgo their Russian investments or interrupt relationships with their Russian suppliers at the onset of the Ukrainian invasion in 2022. In this respect, we do not claim that exiting Russia was the welfare-enhancing choice, but rather that early exits could, on the one hand, receive greater media attention and, on the other, be particularly expensive for shareholders if they were not adequately planned. Our results regarding the directions of influence are consistent, with large institutional shareholders opposing exit decisions and individual shareholders supporting cutting ties with Russia. Second, we extend the scope of our influence mechanism by investigating firms' ESG news coverage

and donations over the last decade. Consistent with our previous findings, large individual shareholding is associated with fewer prosocial incidents and more donations in the AGM month, validating our usage of AGMs for identification.

By providing goods unavailable in the markets, like sanitizing gels to hospitals or pressuring a villain state by terminating business dealings, firms had an advantage over shareholders in creating social value. As large individual shareholders benefited from these firms' responses, pursuing their values implied high costs for the others. Using operating income and market capitalization as measures of these costs, we find that these variables dropped at the most exposed firms by between one and three percentage points. In both cases, these drops are due to increased operating costs, as revenues stayed constant across treated and control firms. Indeed, in the covid case, we find that investment dropped by about 6% in 2020 and 2021 at the most exposed firms, leading to reduced productivity that compiled over time, costing shareholders about 3% of the average earnings-per-share (EPS) in the pre-period.[3] On the other hand, shareholders' influence on the Russian-Ukraine crisis led treated firms to rush out of Russia, with the most exposed firms reneging 20% more investments than control firms. As a result, unheard shareholders suffered: restructuring costs in 2022 eroded 5% of the EPS at the most exposed firms. In conclusion, pursuing the values of a few shareholders costs the others both today and in the future (e.g., Bartlett and Bubb, 2023, Edmans, 2023).

Causally connecting shareholder values with the costs that its pursuit implies on other shareholders is the main novelty of this paper. These findings add to a notable literature examining firms' objectives, which flourished in the 80s when most, if not all, firms claimed to maximize profits (e.g., Grossman and Hart, 1979, Hart, 1995) and that received renewed attention due to the recent transition toward a more sustainable economy and corporate purpose (Edmans, 2021, Rajan et al., 2022). We show that horizontal conflicts (e.g., Ashraf and Bandiera, 2018) across shareholders with misaligned preferences modulate firms' objectives and can impact crucial strategic moves such as breaking ties with partners in a villain state. However, that shareholders (and managers) can extract private rents is not new (Shleifer and Vishny, 1997). The standard solutions are either legal protection of minority rights (La Porta et al., 2002) or the monitoring of large investors (Shleifer and Vishny, 1986, Burkart et al., 1997, Edmans, 2009). Our findings revise the latter point: minority rights are better defended at firms with several large shareholders with heterogeneous preferences than at firms with concentrated ownership around shareholders with similar preferences.

[3]The EPS loss in 2020-21 is over 8% per standard deviation of a firm's share of individual shareholders among its shareholders with at least a 5% stake (ATE). Among the firms with large individual shareholders, an AGM at the onset of the pandemic decreased EPS by 21% (ATT), suggesting sizable costs for unheard shareholders.

Previous works on firms' objectives either model optimal firm's behavior (Fioretti, 2022), exploit experimental evidence (List and Mason, 2011, Duffy et al., 2022, Hart et al., 2022), or are mainly theoretical (Bénabou and Tirole, 2006, Fleurbaey and Ponthière, 2023, Bonneton, 2023): a crucial innovation of this paper is its portable empirical framework, which allows the inference of shareholder preferences from the decisions of large corporations. Without it, we would be left to believe that shareholders did not care for covid interventions since none of the AGM proposals in 2020 at the firms in our sample discussed them. AGM proposals are indeed the standard data for studying questions related to shareholder democracy (e.g., Cuñat et al., 2012, Gantchev and Giannetti, 2021), as they come with detailed information on votes. Although a limit of our approach is that it cannot tell whether managers reacted to shareholders' influence or their expectations, most of the influence is often exercised outside of AGM votes (Gantchev, 2013), making our framework a unique way to study unobserved influence systematically.

This paper also contributes to several recent investigations of shareholder influence through either "exit" and "voice" decisions (Hirschman, 1970, Broccardo et al., 2020, Oehmke and Opp, 2020). The empirical evidence favors voice on sustainability matters as impacting stock prices through stock sales is particularly hard and costly for investors at liquid firms like the large multinationals we survey in our paper (Berk and van Binsbergen, 2021, Saint-Jean, 2023).[4] A large body of literature praises the importance of institutional investors in driving the recent surge in socially responsible investment (e.g., Hartzmark and Sussman, 2019, Chen et al., 2020, Naaraayanan et al., 2021, Yegen, 2020). Our results do not conflict with these works, as factors other than image motives might be at play in other empirical settings.

Our application relates to a broader literature investigating the determinants of corporate donations (e.g., Bénabou and Tirole, 2006, List, 2011, Bonnefon et al., 2022). Related to our results, recent work by Bertrand et al. (2023) finds that, after a merger, the target firm is more likely to lobby the same politicians receiving donations from the acquiring firms (see also Bertrand et al., 2020, Cagé et al., 2021, Colonnelli et al., 2023). In the context of corporate philanthropy, giving is commonly seen as either an efficient advertising tool for profit maximization through increased consumer demand and reduced consumer price sensitivity (e.g., Navarro, 1988, Brown et al., 2006, Elfenbein et al., 2012) or worker productivity (e.g., Tonin and Vlassopoulos, 2015, Gosnell et al., 2020, List and Momeni, 2021), as insurance against reputational risks (Godfrey et al., 2009), as a way to repair sudden reputational issues (Akey

[4]Voice and exit are also studied in relation to stocks' liquidity (Edmans et al., 2013), shareholders' approval of key managerial decisions such as mergers (Gillan and Starks, 1998, Admati and Pfleiderer, 2009), and interactions between consumers and firms (Gans et al., 2021, Ananthakrishnan et al., 2023).

et al., 2021), or as an agency problem within the firms, where managers and insiders extract private benefits to the detriment of shareholders (Jensen and Meckling, 1976, Cheng et al., 2013). Our paper reverses this agency problem by identifying the incentives different shareholders respond to and the distributional consequences of their influence.

The remainder of our paper is organized as follows. Sections 2.2 and 2.3 introduce the conceptual and empirical frameworks, respectively. Section 2.4 presents the main results of shareholder influence using the recent pandemic as our main testbed but also discusses its external validity using the Russia-Ukraine war and the reporting of ESG incidents and donations over the last decade. Section 2.5 illustrates the distributional cost of pursuing shareholder value and discusses our main contributions. Section 2.6 summarises our findings and concludes.

2.2 Conceptual Framework

A firm considers a prosocial action. The action is costly, and adopting it will decrease the firm's profits, thereby lowering the dividends paid to each of its shareholders by $D > 0$. The action is also visible, and one of its two shareholders, shareholder A, will enjoy image gains of $v_A > 0$ due to her connection with the firm. In contrast, shareholder B receives no extra benefits as the public does not associate B with the firm ($v_B = 0$). Each shareholder can pressure the firm's manager to take his or her favorite action, thereby exerting an *externality* on the other shareholder. The probability that shareholders' influences result in the adoption of the prosocial action is:

$$\Pr(\text{prosocial action}) = s(e_A, e_B), \tag{2.1}$$

which is increasing in the influence effort of shareholder A, e_A, and decreasing in that of shareholder B, e_B. The cost of effort to shareholder i, $c(e_i)$, is convex in i's effort level, with $e_i \in \mathbb{R}_+$. The utility to shareholder i is $U_i = (v_i - D) \cdot s(e_A, e_B) - c(e_i)$, so that i's optimal effort sets marginal benefit equal to marginal cost, according to:

$$(v_A - D) \cdot \frac{\partial s(e_A, e_B)}{\partial e_A} = c'(e_A), \text{ for type } A, \qquad \text{and} \qquad -D \cdot \frac{\partial s(e_A, e_B)}{\partial e_B} = c'(e_B), \text{ for type } B.$$

Therefore, A will exert effort only if $v_A > D$: given the expected loss D, we expect shareholders to exert pressure only if they are easily associated with a firm (high v_A). In addition, an *exogenous increase* in v_A will raise A's equilibrium effort. As a result, in the case of strategic complementarities – namely, $\partial^2 U_i / \partial e_i e_j > 0$ – shareholder B will update his effort level to

reduce the probability of a donation.[5] Therefore, the two agents compete on influences and will set the optimal level of effort to offset each other given the dividend loss and their private returns and costs of exerting effort.

This model extends easily to a setting with N shareholders where shareholder $k \in \{1, .., N\}$ is either of type A or B and owns $x^k \in (0, 1]$ shares, with $\sum_{k=1}^{N} x^k = 1$. In this case, the utility of shareholder k of type i becomes $U_i^k = (v_i^k - D \cdot x^k) \cdot s(E_A, E_B) - c(e_i^k)$, where we denote the sum of the efforts of all individuals of type i by E_i. The problem yields similar first-order conditions to the problem with only two shareholders, with a caveat: under strategic complementarities, B shareholders with large shares (x^k) will have the most to lose when shareholders A exert more effort as v_A exogenously increases, leading large B shareholders to intensify their effort more than minority ones. Furthermore, if the public is less likely to associate minority shareholders of type A with the firm, we will expect large type-A shareholders to update their effort levels more than minority shareholders of the same type.

In the real world, shareholders have different effort cost functions for influence and can form different dividend expectations. Imagine that an exogenous treatment increases v_A at some firms but not others: we expect prosocial action to be more likely at treated firms with high shares of type A shareholders owning large shares (blockholders). Similarly, prosocial actions should be less likely at treated firms with larger shares of type B blockholders. In what follows, we infer the externality arising from shareholder influence on observed prosocial actions through the framework displayed in Equation (2.1). To do this, we exploit (i) the AGM timing as an exogenous shock to some shareholders' image gains (v_A) due to increased public scrutiny of their firm and (ii) differences in the public awareness of individual and institutional investors (i.e., financial intermediaries) to categorize shareholders of type A and B, respectively.

2.3 A Quasi-Experiment Through Crises and AGMs

Investigating the nexus between shareholder conflicts and corporate prosocial decisions requires measuring the efforts of different shareholders and observing the prosocial actions taken by the firm, as described in (2.1). Two issues arise. First, environmental, social, and governance (ESG) indices – standard measures of prosociality – are not an adequate dependent variable in (2.1) because they do not provide shareholders with image returns as they do not refer to specific and visible prosocial firms' decisions for which a shareholder might have fought for. Second, we do not observe shareholders' effort levels e_A and e_B in (2.1). Hence, two items are

[5] Strategic complementarities are rather natural in this setting and arise with simple probability distributions like $s(e_A, e_B) = \frac{e_A}{e_A + e_B}$ (with $e_A + e_B > 0$) or the logistic probability.

jointly required: (i) a dataset of visible prosocial actions and (ii) a device shocking only the utility of connected shareholders for some firms (i.e., v_A in Section 2.2).

Crises and Annual General Meetings (AGMs) provide these two items. Widespread crises often lead the public to demand that firms take visible and costly actions. For instance, during the recent pandemic, firms contributed to the relief by donating cash and in-kind through their know-how (e.g., sanitizing gels from chemical firms or specialized software from IT firms). Similarly, the private sanctions on Russia after its recent invasion of Ukraine started even before governmental sanctions. Thus, crises fit our purposes because they provide data about visible actions firms have taken, producing item (i) above, and because they are orthogonal to firm characteristics. However, crises "shock" all shareholders at exposed firms. To get exogenous variation across shareholders, delivering item (ii) above, we take advantage of listed firms' reporting cycles and exploit the occurrence of an AGM as a shock to the media coverage of a firm and its most connected shareholders during crises (v_A from Section 2.2).

AGMs and media coverage. Appendix 2.C provides evidence supporting the claim that AGMs bring greater media coverage by considering NGO attacks on a firm, which, as the firm itself cannot start them, are empirically easier to deal with than corporate donations that can be timed to raise a firm's coverage. We summarize our main findings in this paragraph. First, using data for 2010-2019, Appendix Figure 2.C2 shows that media coverage increases during an AGM period. Second, Figure 2.C3 finds that NGOs are far more likely to start a campaign against a firm in the six weeks around the firm's AGM date.[6] Third, taking the timing of NGO attacks as exogenous, Appendix Figure 2.C4 finds that an AGM period increases news reporting of firms affected by NGO attacks up to 12 weeks away, or 90 days, from an AGM, suggesting that AGM periods trigger greater media attention, which, in turn, can impact the visibility of a firm's shareholders.[7]

Condition for treatment. The AGM timing is exogenous to current events as its date is stable across years. A firm's AGM is the annual gathering of its shareholders; at this meeting, managers present their annual report about the firm's performance, and shareholders vote on previously submitted proposals. If shareholders satisfy certain criteria (see Rule 14a-8 SEA, 1934), they can submit proposals to managers at least 120 days before the release of the proxy statement based on the previous year's AGM (Glac, 2014). Therefore, AGM dates are effectively fixed within firms over time, as shown in Panel (b) of Appendix Figure 2.B1, which finds little

[6]The NGO campaign data come from the Sigwatch database (Hatte and Koenig, 2020), which we describe in Appendix 2.C.

[7]As an illustrative example, Appendix Figure 2.B2 reports a few media pieces featuring prominent shareholders in articles discussing the outcomes of AGM votes.

variation in the AGM month for S&P 500 firms across adjacent years in 2012-2019.

Given that AGM dates hardly change over time, we consider those firms whose AGM period overlaps with the beginning of a crisis as treated. To define an AGM period, we follow the requirements of the Institutional Shareholder Service, the leading firm for proxy voting services to shareholders, which recommends no more than 90 days between the notification of the AGM proposals to shareholders and the AGM date. Therefore, since the first covid case in the US was detected on January 15, 2020 (Holshue et al., 2020), we consider as treated the firms that had an AGM in the first 90 days from January 15, and as control the remaining S&P 500 firms. Analogously, we consider as treated the firms with AGMs set within 90 days from the start of the Russian invasion of Ukraine on February 24, 2022.

Shareholder types. According to our conceptual framework (Section 2.2), the AGM treatment increases the private return of the shareholders that are easily associated with the firm (type *A* shareholders), increasing their willingness to exert effort to influence managers to behave prosocially, but it also raises the opposition of the other shareholders (type *B*).[8] The final outcome depends on the differential influence exerted by the various shareholders. Hence, our empirical approach needs an additional lever as the AGM treatment disregards the composition of the shareholding body.

In our empirical analysis, we label individual and family shareholders as shareholders *A* and financial shareholders like mutual funds as shareholders *B*. We view this distinction as the most objective way to separate shareholders based on whether the public easily links them to a firm: famous individuals, founders, and previous CEOs are included in the *A* category, while financial shareholders like BlackRock and Vanguard invest in most S&P 500 firms (Backus et al., 2021), which detaches them from specific firms in the eyes of the public.

Importantly, including individuals with easy access to a firm's managers like founders (e.g., Bill Gates) in category *A* but not in category *B* is inconsequential for our results because we infer the voice channel as the difference between the *gap* in the adoption rate of prosocial decisions between firms undergoing an AGM period with and without shareholders of type *A* (or *B*) and the analogous *gap* among control firms (with no AGM). The first difference highlights the impacts of the AGM on the effort exerted by shareholders of type *A* (or *B*), while the second difference controls for the effort of shareholders of type *A* (or *B*) after the crisis (i.e., their intrinsic motivation). All idiosyncratic differences across firms, such as the cost of influence or preferences of specific shareholders, vanish by focusing on the difference among these changes at AGM-treated and at control firms as long as the crisis event we focus on and

[8]Other shareholder types include self-ownership, foundations, and national governments or agencies.

the AGM timing are unrelated to shareholders and firm characteristics. This assumption is credible in our setting, as the AGM dates were fixed before the crisis.

Empirical approach. Abstracting from the time dimension for simplicity, we exploit the AGM timing and the ownership structure as outlined in the previous section by translating the contest game described in (2.1) into:

$$y_f = \beta_1 \,\text{Ownership}_f + \beta_2 \,\text{AGM}_f + \beta_{treat} \,\text{Ownership}_f \times \text{AGM}_f + \varepsilon_f. \tag{2.2}$$

The dependent variable, y_f, features the prosocial decision taken by firm f in the 90 days since the beginning of the crisis (e.g., whether it donates for covid). On the right-hand side, Ownership_f is some specific characteristics of the shareholding body of firm f before the crisis, and AGM_f is a dummy for whether the firm planned an AGM in the 90 days after the beginning of the crisis. To illustrate the approach, assume that Ownership_f is one for firms that have individual shareholders and zero otherwise. In this case, β_{treat}, the main coefficient of interest captures the difference in donation rates at AGM-treated firms with and without individual shareholders rebased by the same difference at firms without an AGM: a positive (negative) coefficient suggests that individual shareholders supported (opposed) donations. The next section extends this approach, accounting for fixed effects and the time dimension.

To study the distributional consequences of shareholder influence on other shareholders, Section 2.5 focuses on productivity measures and earnings per share within an intention-to-treat approach. In particular, we translate (2.2) into a difference-in-differences where the beginning of a crisis determines the post-period and the AGM_f and Ownership_f variables determine the inclusion in the treatment. We will carefully examine the pre-trends and evaluate our results using event studies.

2.4 Shareholders' Voice

Our primary focus in this section is shareholder influence at the onset of the recent covid pandemic. The first four sections present the data (Section 2.4.1), the estimation results (Section 2.4.2), and the mechanism (Sections 2.4.3 and 2.4.4). We then discuss the external validity of the voice channel that we uncover using another emergency event (the recent Russia-Ukraine conflict) and an extended period without crises in Section 2.4.5. Section 2.4.6 summarises our main findings.

2.4.1 Data and Balance Checks

We build a dataset on US-based S&P 500 firms collecting information from various sources. Table 2.1 categorizes information in different panels based on their contents. The top panel reports firms' financial and operative characteristics, which we draw from Refinitiv, Orbis, and Compustat. The second panel considers covid exposure at a firm's headquarters-state from Johns Hopkins University (Dong et al., 2020). The third panel focuses on the composition of a firm's shareholding body, zooming in on the shares of individual and institutional shareholders, such as banks, mutual funds, and insurance firms. We only observe shareholders owning at least 0.1% of a firm's equity. This panel pays particular attention to large shareholders. The fourth panel focuses on prosocial characteristics such as Refinitiv's ESG scores and the donation data we hand-coded by sourcing news media outlets, internet searches, and company reports and websites. The last panel states that the condition for treatment is to hold the 2020 AGM before April 15, 2020. AGM dates come from the SEC's N-PX form. Excluding non-US-headquartered S&P 500 firms leaves us with 433 firms. The financial and operational variables are as of December 2019.

Balance checks. Columns 5 to 8 in Table 2.1 presents the summary statistics of the main variables for treated (firms with an AGM before April 15, 2020) and control firms (all other S&P 500 firms). The last column reports the p-values from a t-test of the difference in means: we do not detect substantial discrepancies between the two groups. The firms are very similar across their financial characteristics (e.g., debt, market capitalization, and brokers' recommendations) and operational characteristics (e.g., revenues, EBIT, workforce, number of branches, EPS, and ESG scores). Importantly, for our analyses, despite the institutional control being 14% larger at control than at treated firms on average, treatment and control firms do not differ substantially when we focus on the shares owned by large shareholders, namely, those with more than 5%. The breakdown by type of institutional ownership indicates a statistically significant but economically negligible difference between groups, which disappears when considering only large shareholders. Finally, the share of donating firms within the two groups is approximately the same. Although most firms donate cash and in-kind, the dollar amount does not differ substantially across groups. Overall, these balance checks support the hypothesis that the AGM treatment is indeed exogenous to firms' characteristics.

Sample size. Our sample size is comparable to other studies employing field experiments or surveys – for instance, using samples of similar size to ours, Bassi et al. (2022) quantify the importance of the rental market for production machines in carpentry, Kiss et al. (2023) study the relations between jobseekers' skills, their beliefs, and their job search behavior, and

Bandiera et al. (2013) compare individual and team incentives. However, since most S&P 500 firms hold AGMs in the summer, 53 firms have their AGMs between January 15 and April 15, 2020, or 14% of the firms without an AGM in this period, which are 380 (last panel of Table 2.1). This size difference creates a downward bias in the estimation of the AGM treatment effect, β_{treat}, in (2.2); as a result, our estimates should be interpreted as lower bounds of the actual effect.

2.4.2 Main Results

Before presenting the results, we provide a graphical representation of our empirical approach through an event study regressing whether firm f donated (0/1) between January 15 and April 15, 2020, on weekly dummies for whether firm f held its 2020 AGM in week w, and industry i- and state s-fixed effects:[9]

$$\text{donated by April 15}_f = \sum_{w=\text{Week of Jan 15}}^{\text{Week of June 15}} \beta_w \, \text{AGM}_{w,f} + \sigma_{s(f)} + \iota_{i(f)} + \varepsilon_f. \tag{2.3}$$

The dependent variable does not vary across weeks: a positive (negative) β_w indicates that holding an AGM in week w increases (decreases) the donation rates with respect to the reference week of June 15, 2020.[10] We measure donations by April 15 because the Security Exchange Commission allowed firms to change their AGM date in April, implying that the AGM treatment is no longer exogenous from shareholder preferences for firms planning an AGM for later dates.[11] As in most analyses below, we focus on the extensive margin rather than on the amount donated because almost all firms donated both cash and in-kind. To highlight the trade-off between shareholders that are synonymous with a firm and large institutional shareholders, Figure 2.1 plots the $\hat{\beta}_w$ coefficients estimated through (2.3) on different sub-samples: firms with

[9]The US Government invoked the Production Defense Act in April 2020 to economically support large transformations (e.g., Ford Motors's medical ventilator production). Our dataset spans only voluntary donations, thereby excluding government contracts. As some industries were more likely to engage in government contracts (e.g., the car industry), we control for industries to account for potential biases from lobbying efforts, which, nevertheless, are orthogonal to our AGM timing (Bertrand et al., 2020).

[10]This setup captures about 85% of the AGMs of the firms in our sample. Extending the analysis to the whole year does not affect the results.

[11]The SEC (2020) states that a firm "can notify shareholders of a change in the date, time, or location of its shareholder meeting without mailing additional soliciting materials or amending its proxy materials" under certain conditions. The change took place on April 7; since the seven S&P 500 firms with AGMs between April 7 and April 15 also held an AGM within less than a week from April 7, 2019, it is unlikely that these firms set their 2020 AGM dates based on shareholder preferences relative to covid donations. Panel (a) of Appendix Figure 2.B1 shows that most AGM date changes made in the first four months of 2020 concerned only firms that held AGMs in (late) April 2019.

at least one individual shareholder (blue circles) and firms whose shareholding body is more concentrated towards large institutional shareholders (red triangles) in December 2019.

We note three results. First, donations are more likely at firms with individual shareholders if they hold an AGM before April 15, 2020 (dots). Second, consistent with our theory, institutional blockholders drive the decline in donation rates (triangles) as they expect dividend losses and no private returns from the donations: all else equal, the opposition to covid-donations will be more effective when institutional shareholders own more shares. Third, these two effects die out for firms that have AGMs after April 15, as shareholders at these firms have fewer incentives to influence managers: individual shareholders receive no additional image shock, which does not trigger the response of institutional shareholders.

Treatment effect. What is the effect of holding an AGM at firms with easily associable shareholders compared to the average firm? Table 2.2 estimates (2.2) by OLS, using a dependent variable that is one if firm f donated by April 15 and zero otherwise as in (2.3) and Ownership_f defined either as the share of individual or institutional shareholders with an equity stake that, at December 2019, was either greater than 10% (Column 1 or 4), greater than 5% (Column 2 or 5), or smaller than 2% (Column 3 or 6). Ownership_f is standardized to compare coefficients across columns.[12] Therefore, the treatment and control groups vary across columns. We standardize Ownership_f to compare coefficients across columns and estimate (2.2) with industry- and state-fixed effects.

Focusing on the interaction term, the estimated $\hat{\beta}_{treat}$ is positive and significantly different from zero for individual blockholders (Columns 1 and 2). The coefficient estimates are large as they indicate that the probability of donating increases by more than 9% compared to the average donation rate in the data when the proportion of individual blockholders increases by one standard deviation. Minority shareholders, instead, do not seem to influence company donations (Column 3). These results confirm the predictions of the conceptual framework in Section 2.2, which hypothesized that prominent individual investors that are more easily associated with a firm, such as those with large equity stakes, should receive a greater pass-through of image gains from the donating firm and will exert more pressure to this end.

What about institutional investors? We focus on the three largest institutional investor types in Table 2.1 (banks, mutual funds, and insurance firms) and find consistent results with the predictions of the conceptual framework in Section 2.2. The rightmost columns of Table 2.2

[12]Since S&P 500 firms have few similarly large "blockholders," an alternative specification employing an indicator that is one if the firm has at least one shareholder of type A (or B) with at least $x\%$ shares does not change our results qualitatively, and we omit it. Finally, standard errors are clustered at the industry level to net out potential stochastic shocks across units (Deeb and de Chaisemartin, 2019).

indicate that the probability of donating decreases by approximately 15% of a standard deviation of the share of large institutional blockholders (Column 4) and a negative but insignificant effect for smaller shareholding brackets (Columns 5 and 6). Thus, the largest institutional shareholders pressure managers against donations as their large equity stakes imply they will shoulder a considerable burden from the prosocial actions.[13]

2.4.3 Mechanism

Do Equity-stakes Capture the Association between Shareholders and Firms?

Not all shareholders are created equal: some are easier to associate with a firm than others in ways not reflected in the equity stake. We test whether *i)* individual shareholders are more associated with their firms in their portfolio, and *ii)* this association is even stronger for individual blockholders. We collect the weekly Google trends score of firms and their shareholders from 2018 to 2019, and use the period of a firm's AGM as a shock to media exposure. We test the reaction of the Google trends score of different shareholder types around the AGM of a firm in their portfolio. More specifically, we run:

$$y_{ift} = \sum_{w=-12}^{12} \psi_w \, \text{AGM}_{it+w} + \gamma_w \, \text{AGM}_{it+w} \times \text{Individual}_i + \alpha_i + \tau_t + \alpha_f + \varepsilon_{ift}, \tag{2.4}$$

where the dependent variable is the logarithm of the cumulative Google Trends score over a three-month period starting on week t for investor i. On the right-hand side, the vector $\{\text{News Day}_{it+w}\}_{w=-12}^{w=+12}$ is a set of time dummies around the date of the closest AGM. We further interact these indicators with another indicator variable that is equal to one if shareholder i is an individual investor and zero otherwise. We also include shareholder, firm, and time-fixed effects. We interpret the coefficient vector ψ as the impact of donations on Google searches for nonindividual investors and γ as the gap in visibility between individual and nonindividual investors at each week $t + w$.

Figure 2.2 reports the estimated $\hat{\gamma}$, using cumulative Google Trend scores over twelve weeks as the dependent variable and clustering the standard errors at the firm-by-shareholder level.[14] Panel (a) uses all shareholders as of December 2019. Panel (b) restricts the sample to shareholders with more than 5% of shares. Across both panels, cumulative Google searches are flat at around until 6 weeks before an AGM. In Panel (a), the coefficient estimates jump

[13]Table 2.A1 reports the estimated coefficients for each of the three institutional investor types: opposing influence comes mainly from banks and insurance companies with large shares.

[14]The shareholder types are banks, insurance companies, mutual funds, and individual and family shareholders.

to 7% the week of and after the AGM. As we might expect, the effect is stronger in Panel (b), where the coefficient estimates are already significant a month before the AGM, and jumps to 20% on the AGM week.

The Pass-Through of Image Gains

Our conceptual framework explains shareholder influence through a different pass-through channel of image gains across investor types. Does the data support this hypothesis? To provide direct evidence of a shock to shareholders' private returns, we examine shareholders' media exposure around donation events. We use shareholder names as keywords and run the following OLS regression:

$$y_{ift} = \sum_{k=-10}^{10} \psi_k \,\text{News Day}_{it+k} + \gamma_k \,\text{News Day}_{it+k} \times \text{Individual}_i + \alpha_i + \alpha_f + \tau_t + \varepsilon_{ift}, \tag{2.5}$$

where the dependent variable is the logarithm of the cumulative Google Trends score over a ten-day period starting on day t for investor i in firm f. On the right-hand side, the vector $\{\text{News Day}_{it+k}\}_{k=-10}^{k=+10}$ is a set of time dummies around the date of the donation event. We further interact these indicators with another indicator variable that is equal to one if shareholder i is an individual investor and zero otherwise. We also include firm, shareholder, and time-fixed effects. We interpret the coefficient vector ψ as the impact of donations on Google searches for nonindividual investors and γ as the gap in visibility between individual and nonindividual investors at each day $t + k$.[15]

Figure 2.3 reports the estimated $\hat{\gamma}$, using cumulative Google Trend scores over ten days as the dependent variable and clustering the standard errors at the firm-by-shareholder level.[16] Panel (a) uses only shareholders with at least 1% of shares in December 2019. Panel (b) restricts the sample to shareholders with more than 5% of shares.[17] Across both panels, cumulative Google searches are flat at around zero before the donation news is broken. In Panel (a), after the news is broken, the coefficient estimates jump to about 50% from day 3 to day 10. As we might expect, the effect is stronger in Panel (b), where the coefficient estimates are

[15]For each day, the Google Trends data return a value between 0 and 100 that indicates the frequency of Google searches for a specific keyword based on its long-run searches. Therefore, accounting for shareholder-fixed effects is necessary to compare searches across shareholders.

[16]The shareholder types are banks, hedge funds, insurance companies, mutual funds, other financial companies, individual and family shareholders, government, self-ownership, and other firms.

[17]Since our analysis finds a limited role of minority investors, we consider Google Trends data only for shareholders holding at least 1% of shares. Appendix Table 2.A2 and Appendix Figure 2.B4 show robust results to cumulating the Google Trend data over different time intervals (7, 10, and 14 days).

already significant two days before the news is broken.[18] Therefore, the Google search gains of individual investors are substantially higher than those of nonindividual investors, supporting our claim that image concerns create different incentives for individual and non-individual investors.

Donate Directly or Through the Financial Footprint?

Do financial investors openly oppose covid-related donations? To address this question and to understand the tradeoff faced by institutional investors, we compare the donation decisions of financial corporations in the S&P 500 (e.g., BlackRock and Bank of America) with those of the S&P 500 firms in their investment portfolios.[19] More specifically, we analyze the correlation between two vectors: a vector of donation decisions and a vector of donation shares. The vector of donation decisions is a list of binary dummies, one for each of the 37 financial corporations in our data, indicating whether a corporation donated by April 15, 2020 (19 of them donated). The second vector reports the share of firms in the portfolio of a financial shareholder that also donated. A positive correlation between these two variables suggests an alignment in donation intents between investors and firms, while a negative correlation points to a misalignment. We exploit variation in the AGM treatment statuses of the firms in an investor's portfolio to causally infer whether a donating investor pushes or refrains the firms in their portfolio from donating.

Focusing first on Column 3 of Table 2.3, we find that the correlation coefficient between a firm's corporate giving and the giving within its footprint is positive and even increases across rows, as we raise the minimum shareholding threshold from 0% to 5%. However, no coefficient is statistically significant. This trend may be driven by a few donating firms with larger shares receiving larger weights. Column 2 removes this effect by focusing on simple averages: the correlations are smaller and negative when the minimum shareholding threshold is 2%, 3%, or 4%. Moving to the last column, where we consider only firms with an AGM meeting, we effectively focus on firms whose shareholders might be under the spotlight due to the AGM periods and for which institutional investors might need to pressure managers to prevent individual investors from capturing private rents. As the minimum share threshold increases across rows, the estimated correlation coefficient becomes more negative and statistically significant, approaching -1 for larger thresholds.

[18]The coefficients cannot be directly compared across the two panels because the average number of cumulative Google searches for nonindividual shareholders is twice as high in Panel (b) than (a).

[19]We focus on only S&P 500 firms that invested in other S&P 500 firms due to data availability. However, we expect our result to hold more broadly because it should be more difficult to influence the management of an S&P 500 corporation than that of a smaller one, other things being equal.

These results suggest that, as we tilt the balance of influence from individual to institutional shareholders, the latter shareholders do not necessarily oppose *all* donations, as they donate themselves. They oppose donations at treated firms in their footprint as they do not yield any image gain but (potentially) cost them lower earnings, as we will see in Section 2.5.

2.4.4 Alternative Mechanisms

Intensity of the pandemic. Firms could respond to the need for the donation rather than shareholder pressures. Our empirical approach could miss it if, although unlikely, it is correlated with the AGM treatment. To account for this, we exploit covid cumulative cases and deaths at a firm's headquarters state under the assumption that the severity of the pandemic will provide shareholders with greater incentives to donate even without the AGM treatment. To this end, we modify (2.2) as follows:

$$\begin{aligned} y_{ft} = {} & \beta_1 \text{ Covid Rate}_{ft} + \beta_2 \text{ Covid Rate}_{ft} \times \text{Ownership}_f + \beta_3 \text{ Covid Rate}_{ft} \times \text{AGM}_f \\ & + \beta_{treat} \text{ Covid Rate}_{ft} \times \text{Ownership}_f \times \text{AGM}_f + \alpha_f + \tau_t + \varepsilon_{ft}, \end{aligned} \tag{2.6}$$

where the dependent variable, y_{ft}, is equal to one if firm f has publicly committed to donating by day t and zero otherwise. The main coefficient of interest is β_{treat}, which captures the interaction between the cumulative covid rate at firm f's headquarters state, Covid Rate$_{ft}$, the fraction of equity owned by the reference blockholder, Ownership$_f$, which varies across specifications, and the AGM treatment, AGM$_f$. We use headquarter-state covid rates because Appendix Figure 2.B3 shows a clear spatial pattern across these two variables, with covid-related donations being more likely as the pandemic heightens. Finally, α_f and τ_t are firm- and day-fixed effects, and the standard errors are clustered at the firm level.

The first three columns of Appendix Table 2.A3 present the results when individual shareholders are the reference category, with Ownership$_f$ and Covid Rate$_{ft}$ standardized to facilitate comparisons across columns with different x-blockholding percentages, covid cases (Panel a) and deaths (Panel b). Although the table indicates that one standard deviation in covid rates increases donation rates by about 1%-2%, such an increase is towered by the AGM treatment effect at firms with greater shares of large individual shareholders, β_{treat}, which is estimated between 10 and 20 times larger. In contrast, the treatment effect estimates when the focal blockholder in (2.2) varies across banks, mutual funds, and insurers are negative (Columns 4 to 12) , consistent with the previous results, and the unconditional effect of covid rates is again

negligible.[20]

Financial motives. Abnormal returns do not explain covid-related donations. To compute abnormal returns, we predict daily stock returns using the Fama-French three factors, namely, daily market returns (R_{ft}^{MKT}, proxied by the S&P 500 Index), daily returns on a portfolio of "small minus big stocks" (R_{ft}^{SMB}, from Kenneth French's website), and daily returns on a portfolio of stocks with "high minus low" book-to-market value ratios (R_{ft}^{HML}, also from French's website). We retrieve the betas (β_f) of those three portfolios for the stocks in our sample from CRSP. Then, stock f's abnormal return (AR_{ft}) on day t is given by the difference between the actual excess return of the stock over the risk-free rate (R_{ft}) and the prediction of the 3-factor model, as $AR_{ft} = R_{ft} - (\beta_f^{MKT} \cdot R_{ft}^{MKT} + \beta_f^{SMB} \cdot R_{ft}^{SMB} + \beta_f^{HML} \cdot R_{ft}^{HML})$. We then plug the realized AR_{ft} in the following event study:

$$y_{ft} = \sum_{-5 \leq k \leq 5} \theta_k \text{ News Day}_{ft+k} + \alpha_f + \tau_t + \varepsilon_{ft},$$

where the left-hand side refers to either firm f's abnormal return (AR_{ft}) or its cumulative abnormal return (CAR) on day t. The regression includes firm- and date-fixed effects. Appendix Figure 2.B5 displays the estimates of $\hat{\theta}_k$. Panel (a) shows no abnormal returns before the news is broken, while the abnormal returns are actually negative (although not significant) right after it. Panel (b) reports the CAR over five days, showing a negative drop after the news date.[21] In summary, we find a negative but transient effect of the news on firms' financial returns.

Consumer pressure. We exploit exogenous variation in a firm's exposure to covid through its branches to assess whether consumers pressured firms to donate. Using the Orbis database, we compute the weighted cumulative averages of covid cases and deaths using the number of branches a firm has in each state as weights. We denote the standardized versions of these two

[20]We replicate the analysis using cumulative national covid cases and deaths at the national level instead of at the headquarters-state level as they could be more salient than headquarters-state rates for large financial investors. The results, which we omit because of space constraints, are consistent with those presented thus far, with the only difference being that the estimates for individual and family shareholders are now close to zero. Hence, prominent individual shareholders seem to react to local covid rates rather than national rates. This result aligns well with the image concern mechanism we uncover if these large individual shareholders live or conduct their businesses close to their firms and care for local information (see also Bordalo et al., 2022a).

[21]We find similar results for the CAR over longer horizons (Appendix Table 2.A5).

new variables by Exposure at Branches$_{ft}$ and estimate the following linear probability model:

$$\begin{aligned} y_{ft} = \beta_1 \text{ Exposure at Branches}_{ft} + \beta_{treat} \text{ Exposure at Branches}_{ft} \\ \times \text{ Number of Branches}_f + \alpha_f + \tau_t + \varepsilon_{ft}, \end{aligned} \tag{2.7}$$

where Number of Branches$_f$ is the reported number of branches as of December 2019.[22] The results show a null effect of covid exposure (Appendix Table 2.A4).

Managerial freedom and competition. We proxy managerial freedom with the share of a firm's equity owned by the firm itself and study the probability of observing a donation by time t using (2.6), where we set Ownership$_f$ equal to one if firm f owns more than the median amount of its own shares, and zero otherwise. Since the AGM period provides an opportunity for managers to present their achievements, we use the difference between the treated and control firms to estimate the causal impact of managerial's private or image returns on donations. Although the salience of a donation in a period of crisis can help managers of underperforming firms (Akey et al., 2021, Bordalo et al., 2022b), the results indicate that managers aligned with financial investors in opposing donations potentially because if the donations are costly, as we will see in Section 2.5, managers might see their compensation decrease (Appendix Table 2.A6).

We also study whether firms donated in response to past covid-related donations of a firm's direct competitors by also controlling in (2.6) for a variable that is one if at least one S&P 500 firm in the industry of the focal firm has donated in the previous week and zero otherwise.[23] Our results, presented in Appendix Table 2.A7, show a limited role of competition while the treatment effect coefficients are very similar to those from Table 2.A3. Overall, these findings are in line with other studies suggesting that managers are under pressure to report positive corporate results during AGM periods (Dimitrov and Jain, 2011): large donations can jeopardize a firm's financial position during a time of distress, potentially also affecting managerial compensation.

Missing observations in Orbis. This section has focused on a sample of firms without missing financial and ownership information in Orbis to ensure consistency across the empirical exercises. We replicate our main results – the evidence of influence by individual and institutional shareholders (Figure 2.1 and Table 2.2) and by financial shareholders within their

[22]The distribution of the number of branches for S&P 500 firms ranges from 0 to 13,582 with a median of 40 branches; since we do not know whether a branch is a shop or a factory, it is fair to assume that firms with more branches are more exposed to final consumers than firms with few branches.

[23]We consider competitors' donations in the past week to single out a firms' response to their donations. We obtain similar results using different lags.

portfolio (Table 2.3) – in Appendix Section 2.D using Refinitiv's consolidated ownership data, a slightly larger dataset, that provides historical shareholding information but, unlike Orbis, lacks self-ownership data. Across analyses, not only the signs but also the magnitude of the coefficients stays almost unchanged.

2.4.5 Shareholder Influence Beyond the Pandemic

Does shareholders' influence through voice extend beyond pandemic periods? We test external validity over time and crises by focusing on another time of crisis, the recent Russian invasion of Ukraine in Section 2.4.5 and by using various measures of prosociality over the last decade in Section 2.4.5.

Shareholder Influence and the Russian Invasion of Ukraine in 2022

On February 24, 2022, the President of the Russian Federation, Vladimir Putin, launched the so-called "special military operation," which started with the invasion of Ukraine and quickly escalated to a war that is still ongoing at the time of writing. Soon after that, media scrutiny of multinational corporations intensified as the public questioned the Western firms that continued to conduct business in the attacking country, Russia. As a result, many firms decided to limit their exposure to Russian consumers and businesses, with several exiting Russia altogether. In this section, we study whether a differential pass-through of image gains to individual and institutional shareholders was a factor in these decisions without discussing whether exiting was or was not the socially optimal decision. That is, we view rushed exits as consequential, costly decisions with a significant media impact that could boost the image of synonymous shareholders while costing the others substantially as firms need to pay relocation costs (e.g., suddenly seeking new suppliers and consumers than for planned exits).

Using the same approach outlined in Section 2.4.1, we test shareholders' influence on exiting decisions. Once again, we take advantage of the SEC rules and exploit the occurrence of AGMs as exogenous shocks to firms' scrutiny. To this end, we use a novel dataset that records the actions taken by international corporations vis-à-vis Russia (Sonnenfeld et al., 2022). Through this dataset, we observe the set of US-listed firms that publicly announced actions by March 23, 2022 – a month from the beginning of the conflict (164 firms).[24] These decisions vary

[24]We focus on US-listed firms because the SEC rules apply to US firms. The emphasis is on the first month of conflict because the firms that took action in this period are most likely the most exposed to the Russian market. Focusing on this period also allows us to exclude actions dictated by the ensuing Western sanctions. The vast majority of these firms are in the S&P 500 index and span various sectors of the economy. Online Appendix 2.E describes the data in detail and shows that industries are similarly represented across treated and control firms.

from exiting the country to limiting current and future investments or continuing business as usual. In particular, 51 of the 164 firms in the dataset decided to leave the Russian market. We study this radical decision because of its visibility and salience to the public. Moreover, exiting Russia goes beyond the intention of international sanctions in the first month of conflict, and thus, it was not forced by regulations.

Using (2.2), we identify shareholders' voice on whether to leave Russia by setting the dependent variable, y_f, to one if firm f announced its exit during the first month of conflict and zero otherwise. The regressors are instead, AGM_f, which is equal to one if f held an AGM in the three-month period starting on February 24, 2022, and zero otherwise, and Ownership_f which is equal to one if firm f has either a shareholder of the reference type, either an individual or an institutional shareholder depending on the specification, owning more than the median share of the reference shareholder in the data. We set shareholding data at January 2022 to avoid contamination from shareholder sales. We also include several control variables such as industry fixed effects, broker recommendations, information about geographic sources of revenues, and financial standing at the end of 2021. We provide more information on the covariates and show balance tests in Appendix 2.E.

Table 2.4 reports the results: Columns 1 to 3 refer to individual blockholders, while Columns 4 to 6 refer to institutional blockholders. As in the previous tables, we vary the blockholding thresholds as described in the middle panel: the magnitude of the treatment effect, $\hat{\beta}_{treat}$, increases for higher thresholds. Consistent with previous results, the presence of prominent individual shareholders positively correlates with exits, while the presence of similarly large institutional investors pushes firms' decisions in the opposite direction.

Robustness checks. In Online Appendix 2.E, we perform several tests of these empirical findings. First, we show that the negative β_{treat} coefficient for institutional investors is mainly driven by mutual funds and banks and only partially depends on the influence of insurance company shareholders – a finding that is consistent with those in Table 2.A3. The results also remain unchanged by modifying equation 2.2 to show simultaneous treatment effects by individual and institutional blockholders through the AGM treatment or whether firms that decide for business as usual are included in the analysis. In addition, we obtain similar results when we include all US S&P 500 firms while assuming that the S&P 500 firms not surveyed by Sonnenfeld et al. (2022) took no action against Russia. Finally,exit decisions are not merely determined by the size of the firm, as measured by market capitalization or net income in 2021, indicating scope for shareholder influence.

Impacts on supply chains. Online Appendix 2.E examines supply chains. Drawing from

Factset, which provides information on supply relationships between US and Russian firms, we let the dependent variable in (2.2), y_f, be one if firm f reduced ties with Russia after February 24 and zero otherwise. Despite the size of the dataset, which covers only 102 firms with supply chains in Russia before February 24, 2022, we find that large individual shareholders indeed demanded to cut Russian suppliers.

Shareholder Influence Beyond Crises

Is shareholder influence on prosocial matters only limited to crisis events? We examine this question by studying firms' ESG-related news coverage and donations during AGM periods across firms with different shares of individual shareholders. We expect the change in these variables to be only temporary because shareholders' reputation gains should be limited to the AGM period if they drive influence.

Data. ESG-related news data come from RepRisk for 2011-2021. RepRisk screens over 80,000 media, regulatory, and commercial documents daily in fifteen different languages for adverse ESG issues called "incidents." We focus on incidents because favorable news may come from greenwashing. Charitable donation data comes from Ravenpack, which similarly gathers news about millions of entities worldwide and identifies news about donations made by US corporations between 2011 and 2021. We merge this data with historical shareholding information from Refinitiv to get the firms' shareholder compositions over the period. Finally, we source AGM dates from ISS. The resulting ESG-incident dataset covers 642 firms over eight years. The average firm had 772 ESG incidents in this period, of which 651 pertained to the social ("S") category. The donation dataset spans 988 firms over 11 years, 760 of which made at least one donation for a total of 4,439 donations. The firms in the resulting datasets account for over 90% of the market capitalization of the original Ravenpack and RepRisk datasets (Appendix 2.F describes the sample selection).

Methodology. Once again, we exploit the exogeneity of the dates of AGMs to test whether the presence of individual blockholders is associated with prosociality. Exploiting the fact that shareholders have until 120 days before the date of the release of the proxy statement of the previous AGM to submit proposals for the current AGM, we distinguish two periods: a pre-period, during which formal proposals can be cast, and a post-period, during which shareholders can engage only informally with managers and board members. We also consider two groups of firms based on their level of individual and institutional blockholders. To operationalize this analysis, we need to overcome two issues: (i) AGM dates vary across firms within a year, and (ii) firms have AGMs every year – i.e., repeated treatment. To address the

first concern, we modify the calendar time of each firm so that the third month before its AGM date coincides with month 0. The pre-period starts in month -4 and ends in month 0, while the post-period lasts from period 0 to 7. Thus, a year still consists of 12 months and starts seven months before the AGM date for all firms. To address the second challenge, we stack all our yearly difference-in-differences analyses over the years as proposed in Cengiz et al. (2019). We focus on the following event study regression:

$$y_{fmt} = \sum_{\substack{k=-7 \\ k\neq -4}}^{4} \lambda_k \, 1_{\{m+k,t\}} \times \text{Treat}_{ft} + \mathbf{X}_{fmt}\,\beta + \alpha_{ft} + \tau_{mt} + \varepsilon_{fmt}, \tag{2.8}$$

where to avoid double counting the same news, we define y_{fmt} as an indicator that takes a value of one if firm f placed at least a donation (or had an S-incident) in rebased month m of year t and zero otherwise. Treat_{ft} is an indicator that depends on firm f's ownership at the beginning of the year t – we define it in the next paragraph. Thus, we control for endogenous variation in stock ownership by holding this variable constant within each year. As customary in an event study, we interact this variable with $1_{\{m+k,t\}}$, which is one in month $m+k$ of year t and zero otherwise. We also include this variable in $\mathbf{X}_{fmt}$ to adequately control for AGMs' calendar dates as, for instance, AGMs in April and December could raise different media attention. In addition, we control for lagged quarterly cash holdings (in logs) and leverage to account for financial resources, which could vary across time and firms. Since (2.8) stacks multiple yearly difference-in-difference estimators, the fixed effects are at the firm-by-year, month-by-year-by-state, and month-by-year-by-industry levels. Standard errors are clustered by firm.[25]

Results. Figure 2.4 presents the $\hat{\lambda}_k$ coefficients from estimating (2.8) by OLS: Panel (a) studies donations and Panel (b) social incidents. Each panel reports the estimates from two regressions based on the definition of Treat_{ft} in (2.8). The blue dots define firms with prominent individual shareholders as treated. Red triangles consider firms with prominent institutional and no individual shareholders treated.

We start with a null result. The red triangles never differ from zero around an AGM period. Consistent with the conceptual framework in Section 2.2, institutional shareholders do not exert influence against corporate prosocial behavior if they expect no shareholders to extract private gains (i.e., individual shareholders). In contrast, we observe that treated firms with individual shareholders (blue dots) are associated with prosocial actions around the AGM

[25]The recalendarization forces all AGMs to happen at the same time, which prevents the negative weighting of some AGMs that can occur with staggered designs (Sun and Abraham, 2021).

month ($m = 0$). Panel (a) shows a statistically significant increase of 3 percentage points in donations during that month, meaning a 60% increase in the probability of observing a donation in a month. This effect is transitory and concentrated around the AGM month when media attention heightens (see Online Appendix 2.C), and individual investors can get private returns.

The evidence is more nuanced in Panel (b). In line with our mechanism, firms with individual shareholders (blue dots) statistically have fewer social incidents only during the AGM month. However, although insignificant, the estimated coefficients are negative in all periods. To reconcile this finding, note that the social category includes not only "donations" and other readily actionable items like "violation of national legislation," for which a prominent shareholder may exert influence in expectation of negative publicity when the firm is under the spotlight. Items like "social discrimination" and "corruption, bribery, extortion, and money laundering" are issues that might require structural changes. These items are not immediately visible to the public and might confound our results for the social category.

2.4.6 Summary of Results

This section empirically tested the theoretical framework outlined in Section 2.2 using the pandemic as the main testbed. Our main results suggest that the balance between a shareholder's private returns and the potential earning loss due to the adoption of visible but costly prosocial decisions incentivizes shareholders to pressure managers in different directions. Exploiting AGM timings as a shock to a shareholder's private returns, we find that individual shareholders, who are synonymous with a firm, push for greater adoption of prosocial measures (Figure 2.1). This result is robust to different ways of measuring the closeness of the link between a firm and its shareholders (Section 2.4.3). We support the idea of a different pass-through of image gains between individual and institutional shareholders by showing a substantial gap between Google searches of individual and institutional shareholders (Section 2.4.3). At a time of crisis, large institutional shareholders are instead those who could potentially suffer the most from costly prosocial corporate interventions if they negatively impact profits and future growth prospects of the firm they invested in. As a result, our methodology infers that these shareholders oppose donations at the footprint (Figure 2.1); yet, these shareholders are not necessarily against prosocial behaviors such as covid-related donations if they can reap the publicity benefits of being the donor (Section 2.4.3). In doing so, our analysis rules out several alternative channels, such as financial returns, consumer pressure, and managerial preferences (Section 2.4.4).

Our results are local average treatment effects because of the nature of the crisis shock. However, our findings are not limited to the pandemic: applying our framework to data from the onset of the conflict between Russia and Ukraine leads to similar conclusions (Section 2.4.5). Moreover, by exploiting firms' ESG news coverage and donations over the last decade, we provide evidence that similar private returns incentivize individual shareholders to influence firms' behaviors during non-crisis periods too (Section 2.4.5). Thus, our framework does not necessarily require a crisis to infer influence but only to interpret the underlying mechanism.

Finally, our framework only infers influence: we have no way to see whether actual influence took place – for instance, no shareholder proposal in 2020 considered covid-related donations – or whether managers responded to the expectation of influence from shareholders. Still, we know that managers responded to characteristics of their shareholding bodies due to the AGM treatment in a way that is consistent with shareholders' voice over prosocial changes. How much is the cost of these positive changes for "silent" or "unheard" shareholders? We turn to this question next.

2.5 The Shared Costs of Influence

What are the implications for "unheard" shareholders of some shareholders' influence on managers? Consider a simple setting where a firm has R revenues and C operating costs; its operating income is $\pi = R - C$. The firm can either reinvest π, which would contribute to future operating income, distribute it as a dividend to its shareholders, or surrender to shareholders' voice and spend it in non-productive ways such as a donation (as in Section 2.4) or a disorganized exit from Russia (as in Section 2.4.5). If the firm opts for the non-productive choice, the discounted value of future operating incomes could drop, resulting in a net loss for all shareholders who cannot extract private benefits from it (e.g., image returns).

Measuring a firm's productivity is generally tricky. Nevertheless, we have access to two variables that, together with the shocks provided by the exogenous timing of AGMs and external crisis, ease our identification problem: operating income and market capitalization.[26] The first variable speaks directly about how much revenue a firm can raise for each dollar spent in costs and is often used as a row measure of productivity, given demand (e.g., Harberger, 1954, Baqaee and Farhi, 2020). The second one provides insight into the discounted loss to shareholders through changes in stock prices.[27]

[26]Dividend policies make dividends not a viable measure of rent extraction (e.g., La Porta et al., 2000).

[27]An alternative approach would incorporate our AGM treatment in a full production function model à la Olley and Pakes (1996) to describe and test how different firms' decisions impact production. However, a similar

As productivity impacts both R and C, we cannot identify productivity changes without accounting for changes in demand affecting R, and there are reasons to believe that consumer demand reacted both to covid and the invasion of Ukraine through lockdowns and consumer protests. However, it is safe to believe that potential demand changes are unrelated to the share of individual and institutional shareholders before the crisis (Section 2.4.4). Our approach employs a triple differences-in-difference estimator, which leverages this intuition. We consider a firm as treated if it held an AGM at the onset of the crisis and control otherwise. We then distinguish firms into two more groups based on whether they had large individual shareholders just before the crisis. Identification only requires that the relative change in outcomes between firms in the two groups trended similarly for treated and control firms, a milder requirement than for standard difference-in-differences model (Olden and Møen, 2022).[28]

2.5.1 Data

We perform our analysis on two samples. The first sample exploits the pandemic and focuses on the 1,000 largest US-listed firms just before the pandemic hit the country (December 2019) to study their productivity between 2013 and 2022. For the Ukraine invasion case, instead, we restrict our analysis to quarterly data between 2020 to the third quarter of 2022 to capture the immediate effects of a disorganized exit from Russia. We further restrict our sample to firms that dealt with Russian counterparts before 2022, excluding those with no revenue from Russia, according to Refinitiv, because these firms are impacted only indirectly by this crisis. The final sample consists of the largest 1,153 US-listed firms with dealings with Russia. Therefore, the first sample includes much larger firms than the second one, with operating income and market capitalization four times greater on average. The Ukraine-Russia sample is also more heterogeneous, displaying operating incomes almost two times more skewed than in the covid sample. In both samples, historical ownership and financial data are from Refinitiv and Compustat, while AGM dates are from ISS.

exercise might be daunting because it would require modeling shareholder influence and product- and plant- or production technology-level data for the large multiproduct firms we focus on (e.g., De Loecker, 2011, Boehm and Oberfield, 2020, Fioretti and Tamayo, 2021).

[28] In particular, our approach does not require that the parallel trend holds for each difference-in-differences (DD) that builds our triple DD estimator (the difference between AGM-treated and control firms with individual shareholders and the same difference for firms without individual shareholders). For example, even though NGOs' campaigns are more likely during a firm's AGM period, potentially impacting its demand, they do not affect identification as long as their attacks are unrelated to the identity of a firm's shareholders – this conclusion automatically extends to other unobserved factors. Before estimation, we also check that treatment heterogeneity in each DD of the triple DDs in Figures 2.5 and 2.6 is not a concern (De Chaisemartin and d'Haultfoeuille, 2020).

2.5.2 Methodology and Results

Crisis 1: Covid Pandemic

Starting from the covid crisis, the left panels of Figure 2.5 display quarterly average operating income and market capitalization by group and treatment condition between 2016 and 2022. Treated (control) firms are displayed with solid (dotted) lines, and firms with (without) large individual shareholders are in bold blue (red). The average trends by groups look parallel, especially in the years immediately before 2020. In contrast, especially in 2020 and 2021, the gap between the bold blue and red solid lines widens while that between the two dotted lines shrinks: we infer that operating income and stock prices dropped at the firms where shareholders had the most to gain from prosocial actions, highlighting negative consequences for other shareholders.

To assess magnitude changes, the right panels estimate the following event study:

$$y_{ft} = \sum_{k \neq 2019} \theta_k \; 1_{\{t+k\}} \times \text{Treat}_f \times \text{Ownership}_f + \mathbf{X}_{ft} \; \beta + \alpha_f + \tau_t + \iota_{i(f)t} + \varepsilon_{ft}, \tag{2.9}$$

where the dependent variable is operating income or market capitalization (in logs). As in Panel (a), Treat_f are the firms that held an AGM in the 90 days after January 15, 2020, and Ownership_f is the share of individual shareholders with at least a 5% equity-share, which we standardize to interpret θ_k in terms of standard deviations in individual ownership.[29] The direct effect of ownership and treatment status in each month $t + k$ is accounted for in $\mathbf{X}_{ft}$, which also includes lagged assets to control for variation in firm size. The fixed effects are at the firm, α_f, year, τ_t, and industry-by-year, $\iota_{i(f)t}$, levels, with the latter capturing the average impact of the crisis across industries. The regression residuals are likely correlated within states (e.g., state policy) and across firms in the same industry (e.g., demand responses). Thus, we cluster the standard errors at these levels.

Panels (b) and (d) measure the effect of shareholders' voice on productivity. Operating income dropped immediately in 2020 by \$81m of a standard deviation and dropped further in 2021 by \$359m (p-value: 0.09) before returning to its pre-covid values. On average, we estimate in Appendix Table 2.A8 that a 1% increase in the share of individual investors with at least a 10% share costs the other shareholders less operating income for \$130m (p-value $\leq$ 5%). A similar increase in the share of individual investors owning 5% leads to a more modest \$76 m loss (p-value $\leq$ 5%). The average treatment effect can be summarised in a -1.7% in yearly operating income. In addition, we find that the loss is entirely driven by concentration among

[29] We winsorize this variable at the 99% percentile to deal with outliers.

large individual shareholders (cf. Columns 1 and 3 of Appendix Table 2.A8), further validating the mechanism exposed in Section 2.2.

Mechanism: fewer investments at treated firms. Operating income could drop because of greater costs, C, or less revenues, R. Appendix Figure 2.B6 shows that sales as a fraction of total assets stayed constant at treated and control firms, while the fraction of total assets covered by operating income declined sharply after 2020, a finding that resonates well with our results in Section 2.4.4 indicating that consumer demand did not impact covid donations. As donations are costly, Appendix Figure 2.B7 finds that shareholders' voice decreased a firm's cash holding in 2020 and 2021. Less cash led to fewer investments, especially in the manufacturing sector, where total investments dropped by between 4% and 10% (p-value $\leq$ 0.08) of a standard deviation, compared to 2019 (Appendix Figure 2.B8). As a result, shareholders at treated firms immediately felt the cost of the decline in productivity. Panel (d) of Figure 2.5 shows a steady decline in market capitalization by between 5% and 8% of a standard-deviation.[30] This average loss to shareholders is substantial: Column 3 (4) of Appendix Table 2.A8 measures it in a 4% (3%) change per 1% increase in individual shareholders with at least 10% (5%) share.

Crisis 2: Invasion of Ukraine

Figure 2.6 replicates the analysis using the Ukrainian invasion as a testbed. Panel (b) runs an event study similar to (2.9) on quarterly operating income. Because of skewness and negative values in quarterly operating incomes, we present results after applying an inverse hyperbolic transformation to the dependent variable.[31] In the first quarter of 2022, the coefficient estimated for the transformed operating income dropped by about 10% of its average value before 2022 per each standard deviation of the share of individual blockholders, before recovering by Q3 2022. As for the covid crisis, we find that shareholders faced an immediate loss as the stock market of the most exposed firms to individual shareholders' voices dropped by 6%-8% of a standard deviation in each quarter after the crisis broke. The cost to shareholders is similar to that from the covid crisis, measurable in 1% of quarterly market capitalization for a 1% increase in individual blockholding (Appendix Table 2.A8).[32]

[30] Market capitalization as a fraction of total assets dropped by between 5 to 16% at treated firms – Panel (a) Appendix Figure 2.B9.

[31] Since the transformation used in Panel (b) of Figure 2.6 is $\ln(x + \sqrt{x^2+1})$ and approximates the log-transformation well when $|x|$ is large we measure operating income in dollars rather than in millions of dollars (Bellemare and Wichman, 2020). Appendix Figure 2.B10 experiments with other concave transformations and finds a quantitatively similar drop in Q1 2022.

[32] The samples in Sections 2.5.2 and 2.5.2 are different, so we cannot directly compare figures, with yearly average operating income and market capitalization four times larger in the covid sample.

Mechanism: restructuring costs. As before, we investigate changes in revenue or costs as the main source of the loss observed at treated firms. Appendix Figure 2.B11 finds that operating income as a fraction of assets dropped substantially while sales remained constant, indicating that the costs of rushing out of Russia, such as finding new suppliers as suggested in Section 2.4.5, tower the lost Russian revenues. This interpretation is also consistent with the timing of the government sanctions that eventually imposed no dealing with Russian entities for most, if not all US firms, so we can conclude that rushed exits did not cost in terms of consumers as much as it increased costs. What are these costs? Fleeing past investments, potentially at a highly discounted price or loss, might be a credible hypothesis. Consistent with it, Panel (a) of Appendix Figure 2.B12 finds that treated firms sold their past investments at a substantially higher rate than control firms: 20% more sales per standard deviation increase in the share of individual blockholders in each quarter after the crisis.[33] The associated costs are visible in Panel (b), which plots the differential evolution of the cash-to-asset ratio, highlighting a drop as high as 3% per standard deviation of the share held by individual blockholders.

2.5.3 Discussion: "The Cost for Unheard Shareholders"

In the previous sections, we inferred that highly visible and potentially connected shareholders motivated by personal interests seek to extract rents by influencing firms to take visible but costly prosocial actions. By assessing their distributional cost across the shareholding body, this section estimates a "welfare cost" of shareholders' voice without engaging in a formal welfare analysis that would be far-fetched without data to assess the social benefit of an extra in-kind donation. We find that shareholder influence has non-negligible distributional consequences for "silent" shareholders: our intent-to-treat framework estimates an average treatment effect of -1.7% in yearly operating income and -3.36% in market capitalization for the covid case. The drop is even starker among treated firms, which lost about 7% of yearly operating income. Despite a different mechanism, the Ukraine-Russia case finds slightly smaller but comparable drops in quarterly operating income and market capitalization.

The sudden timing of these drops in key productivity measures is consistent with the proposed mechanism. Based on quarterly data, the Ukraine-Russia case illustrates the timing effect well: the drop in operating income is in the quarter immediately after the invasion (Figure 2.6), and it reverberates in a steady decline in market capitalization across all quarters of 2022 at treated firms. We find that the increase in operating costs is related to relocating

[33] As a result, the ratio between equity and total assets, depicted in Panel (b) of Appendix Figure 2.B9, remained constant in the post-period.

activities and selling past investments in a disorganized manner: Panel (b) of Figure 2.B13 finds that restructuring charges reached $0.3 per share more at treated than at control firms after the invasion, or 5% of the average pre-crisis earnings per share (EPS), which measure the net income distributed to each outstanding share.[34]

In contrast, the yearly data in the covid case allow us to investigate how influence dynamically impacts future shareholder outcomes. The mechanism still relies on changes in investments. However, this time, in-kind donations reduced cash flows by imposing variable operating costs (e.g., inputs and personnel) without increasing revenues. These expenses ate resources that would have been otherwise available for future investments: Panel (a) of Figure 2.B13 shows that EPS dropped in 2020 and 2021, two years after the start of the pandemic, by about $0.4 - $0.8 more at treated firms, or over 8% of the average EPS in 2019.[35] Thus, influence does not only cost shareholders a portion of their current potential payoffs but also future ones. We conclude that those shareholders who could not yield private benefits from the firms' prosocial actions made overall a loss. Thus, shareholder influence, even on ESG matters as "trivial" as donating to fight COVID-19, has substantial distributional consequences.

This paper brings new data and empirical methods to normative questions regarding what firms should do in similar situations (Friedman, 1970, Baron, 2007). While some positive corporate decisions could create value for society at large – i.e., corporate donations to hospitals of items such as face masks that shareholders would have been unable to procure themselves – and thus, it might be optimal from a societal point of view that firms undertake them as discussed in a seminal paper by Hart and Zingales (2017), we find that not all shareholders value them equally. As suggested by Bartlett and Bubb (2023) and Edmans (2023), for corporations to have social responsibilities beyond the profit motive, shareholders must support corporations' socially responsible actions; without it, managerial decisions do not represent shareholders' values and create tensions among shareholders. Given that only major issues or disagreements make it to AGMs for voting, most shareholder disagreements are unobservable to outsiders. To determine whether shareholders support these actions, we develop a portable framework to infer shareholder preferences about corporations' socially responsible actions. When considering large corporations with diffuse shareholders, the losers among the shareholders (e.g., households saving through financial intermediaries) can potentially be many more than the actual winners.

[34]The estimates in this section should be interpreted per standard deviation of the share of individual blockholding, as discussed when we introduced the triple-difference equation (2.9) in Section 2.5.2.

[35]In absolute terms, the average loss in EPS was 2.7% (i.e., ATE) of the average pre-covid EPS for treated firms with large individual shareholders ($\geq$ 10%); among these firms, an AGM at the onset of the pandemic led to less EPS by 21% (i.e., ATT).

Extending the spectrum of our analysis, shareholder conflicts might also have welfare consequences for other stakeholders, such as workers, consumers, or the environment, effectively implementing a redistribution toward social causes (e.g., Baron, 2001). In these cases, managerial decisions could overweight or underweight the payoff to concerned stakeholders compared to the objective of an elected representative, as, for instance, managers might respond to stock prices or their stock options, matters that are of no concern for elected officials. Therefore, the mere existence of a positive or negative externality (e.g., the potential to enact private sanctions on a villain state) does not authorize managers to solve it (Edmans, 2023). More research is needed to assess the consequences of heterogeneity across shareholders' values and influence for other shareholders and society at large, both empirically (e.g., Allcott et al., 2022, Fioretti, 2022) and normatively (e.g., Hansmann, 2000, Elhauge, 2005, Broccardo et al., 2020).

"Who watches the watchmen?" Despite uncovering unobserved tensions among shareholders, we do not believe that shareholders should vote on each possible action: this would not only be impractical, but it also defies the very reason for having a qualified management team. Nevertheless, there are several ways for managers to learn about their shareholder preferences. For instance, most companies meet with their largest shareholders regularly (Edmans, 2023). Even without meetings, some shareholders are particularly vocal about their values, as shown by Bill Ford in the introduction to this article, meaning that shareholders are aware of each other's preferences. Our results indicate that large shareholders monitor each other and anticipate each other's motives to influence managers. The monitoring is triggered by (i) the balance of shareholder preferences, (ii) the cost of their influence on managers, and (iii) the potential future earning losses (see Section 2.2). Therefore, shareholder preferences matter for a firm's efficiency and the protection of minority rights. In past years, an extensive literature has developed investigating the pros and cons of the monitoring role over managers of a firm's largest shareholders (e.g., Shleifer and Vishny, 1997). Our findings refocus this literature around the preferences of large shareholders: since only large shareholders might have enough to lose from mismanagements, they have incentives to monitor managers and shareholders; if all large shareholders have the same preferences, they might all seek the same rents at the cost of minority shareholders and other stakeholders (e.g., workers). Hence, heterogeneity among blockholders creates value for minority shareholders, a hypothesis that future research could test using stock market data.

Empirical contribution. We also contribute methodologically to the debate about shareholder preferences by providing a framework that links (specific) shareholder preferences to firms' prosocial actions to infer the unobserved pressures exerted by shareholders on managers.

Moreover, the proposed framework is portable across time and countries (see Sections 2.4.5 and 2.4.5). On the other hand, standard techniques studying AGM votes would not teach us much regarding shareholder preferences, as most shareholder conflicts might not emerge at AGMs – for instance, no shareholder was called to vote upon covid donations at AGMs in 2020.

This new framework opens several avenues for future research as our approach cannot tell whether managers react to the realized pressure or influence of some shareholders or whether they react to this expectation. Addressing the determinants of these managerial expectations is necessary for policies aiming at improving governance and communication between stakeholders. Behaviorally, shareholders' preferences can be micro-founded through a warm glow utility as in Andreoni (1989) or reputation concerns as in Bar-Isaac et al. (2008). One possible way to empirically distinguish these two channels is to exploit repeated shocks to learn whether a shareholder's influence declines over time – conditional on not selling her shares – as her reputation gains reach a plateau, which would be consistent with signaling. However, this exercise is infeasible with our data, as we take advantage of single large sudden shocks, and thus, we view these motives as externalities that shareholders inflict on other shareholders.

Thus, while our framework is suitable for establishing causality, it might not be able to assess shareholder welfare changes in different counterfactual scenarios. For example, policymakers might ask about firms' behaviors and total welfare changes if policies reducing coordination costs between managers and shareholders (e.g., Aghion and Tirole, 1997, Landier et al., 2009, Harris and Raviv, 2010) or different managerial compensations (e.g., Baker et al., 1988, Bandiera et al., 2009, Saint-Jean, 2023) are in place. A complete model of shareholder preferences might help in this case: this requires modeling the purely altruistic preferences, which we do not discuss in this paper because they are net out by the control group, and understanding the root of shareholders' private gains. We view these questions as fertile grounds for future research.

In conclusion, the transition toward a more sustainable economy expands the source of rents for shareholders by adding new concerns, such as private image gains, to already existing ones, like profit motives. As the quote by Grossman and Hart (1979) in the introduction states, our study suggests that today it is more important than ever that "the manager of a firm [...] not only [...] organize production, but also learns about the preferences of the firm's shareholders." We view this paper as a first step in this direction.

2.6 Conclusion

Stakeholders influence a firm's strategy. This paper offers a portable framework that exploits quasi-experimental variations commonly available at all listed corporations to investigate how shareholders, a central stakeholder, impact firms' strategies over visible but costly prosocial decisions. We apply our framework to corporate decisions to donate for covid relief during the pandemic and to exit the Russian market as a private sanction after Russia invaded Ukraine. In both settings, the prosocial decision is optimal for shareholders if they care for the issue at stake; for instance, a large chemical corporation might be in a better position to provide sanitizing gels and facemasks during the pandemic than what the donations of a shareholder to an NGO can buy. However, what is the optimal action if shareholders have different preferences?

We show that firms are more likely to adopt costly prosocial changes if their shareholding body includes easily recognizable individual and family investors. In contrast, significant financial shareholding had the opposite effect on corporate donations. We explain the different influences exerted by these shareholders in terms of a heterogeneous pass-through of image gains to a firm's shareholders using internet search data. Thus, shareholders face different tradeoffs because they have different preferences: all shareholders bear the cost of a firm's decision, but only some derive positive image gains. As a result, pursuing "shareholder value" might come at a cost for other shareholders. Consistent with this hypothesis, we find a significant and sustained drop in productivity after the pandemic and the Russian invasion. We exploit the different features of the two crises to investigate and interprete different channels for shareholder influence to negatively affect productivity and provide evidence that large shareholders monitor each other.

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Table 2.1: Firm and shareholder characteristics at treated and control groups

	Quantiles			Average				
	25%	50%	75%	Overall	Treated	Control	Diff.	p-value
	(1)	(2)	(3)	(4)	(5)	(6)	(5)-(6)	(8)
i. Firm characteristics								
Revenues (bn $)	5.16	10.32	22.44	27.00	26.84	28.42	-1.60	0.82
Share of revenues from the US (%)	15.00	19.63	25.42	20.03	19.99	20.42	-0.40	0.82
EBIT to revenue	0.09	0.16	0.23	0.16	0.16	0.13	0.00	0.14
Earnings per share, EPS ($)	2.07	3.91	6.19	4.78	4.83	4.41	0.40	0.44
Workforce (headcount, thousands)	8.55	18.80	55.30	54.00	53.39	59.81	-6.40	0.63
Number of branches	9.00	40.00	171.00	310.52	310.19	313.42	-3.20	0.98
Total debt (bn $)	3.40	7.18	16.51	16.02	16.53	11.78	4.80	0.13
Interest expenses (m $)	28.00	59.83	142.00	121.20	125.25	88.62	36.60	0.08
Market capitalization (bn $)	13.22	23.85	50.52	60.05	57.77	80.12	-22.40	0.42
Brokers' recommendations [-2,2]	0.32	0.62	0.87	0.58	0.58	0.61	-0.00	0.72
ii. Covid exposure								
Covid cases at HQ state (thousands)	15.85	28.89	52.92	69.52	71.79	49.58	22.20	0.04
Covid deaths at HQ state (thousands)	0.78	1.27	2.45	4.70	4.91	2.85	2.10	0.02
iii. Shareholding composition								
Individual ownership (%)	0.00	0.00	0.09	1.38	1.37	1.47	-0.10	0.93
Institutional ownership (%)	40.52	46.89	52.78	46.47	47.08	41.13	5.90	<0.01
- Banks (%)	29.18	33.58	38.92	33.69	34.20	29.37	4.80	<0.01
- Mutual Funds (%)	4.61	6.64	9.92	7.98	8.00	7.80	0.20	0.74
- Insurance Companies (%)	2.59	3.65	5.46	4.66	4.76	3.81	0.90	0.02
Shares owned by individuals with > 5% (%)	0.00	0.00	0.00	2.31	2.34	2.12	0.20	0.90
- excluding firms w/out indiv. with > 5% (%)	32.86	62.77	81.88	59.95	60.36	56.26	4.10	0.83
Shares owned by institutions with > 5% (%)	38.48	51.28	62.55	49.00	49.87	41.43	8.40	0.09
- excluding firms w/out inst. with > 5% (%)	42.10	52.73	63.73	53.44	53.18	56.31	-3.10	0.50
iv. Prosocial characteristics								
ESG scores [0,100]	49.69	63.05	72.83	61.10	60.95	62.46	-1.50	0.49
Share of firms donating by April 15 (%)	0.00	0.00	100.00	43.05	42.58	47.17	-4.60	0.53
Amount donated (m $)	1.00	6.50	26.00	42.44	44.19	28.89	15.30	0.40
Amount donated to revenue (%)	0.01	0.03	0.11	0.13	0.13	0.15	-0.00	0.84
Amount donated to dividends (%)	0.19	0.55	1.65	2.18	2.25	1.64	0.60	0.50
i. Definition of the treatment group								
AGM date relative to April 15	-	-	-	-	Before	After	-	-
Number of firms	433	433	433	433	53	380	-	-

Note: The first three columns present summary statistics of the principal characteristics of the firms in our sample and their shareholders. The last five columns report average values for the whole sample (Column 4), for firms with an AGM before April 15, 2020 (Column 5) and for firms with an AGM after April 15, 2020 (Column 6), their differences (Column 7) and p-values (Column 8). The accounting and financial data are measured on December 31, 2019. Avg. Brokers' Recommendations is the average of equity analysts' investment recommendations where strong sell is -2 and strong buy is 2.

Table 2.2: Shareholders' influence on covid donations

	Whether Firm f has Donated (0/1)					
	(1)	(2)	(3)	(4)	(5)	(6)
Ownership	0.014	0.018	−0.036*	−0.014	−0.014	0.055*
	(0.017)	(0.011)	(0.020)	(0.025)	(0.026)	(0.029)
AGM	0.095	0.097	0.089	0.082	0.083	0.092
	(0.099)	(0.099)	(0.102)	(0.081)	(0.104)	(0.101)
Ownership × AGM	0.093***	0.096**	−0.013	−0.150***	−0.021	−0.033
	(0.021)	(0.034)	(0.042)	(0.043)	(0.066)	(0.065)
Ownership is defined as	Individuals			Institutional		
Ownership is the share of investors owning:	$> 10\%$	$> 5\%$	$(0\%, 2\%)$	$> 10\%$	$> 5\%$	$(0\%, 2\%)$
Industry fixed effects	✓	✓	✓	✓	✓	✓
State fixed effects	✓	✓	✓	✓	✓	✓
N	433	433	433	433	433	433
Adjusted R-squared	0.1595	0.1599	0.1597	0.1668	0.1562	0.1657

* $- p < 0.1$; ** $- p < 0.05$; *** $- p < 0.01$.

Note: The table presents the coefficients from OLS regressions of an indicator variable that is one if firm f has donated by April 15, 2020, on covariates. Italicized variables are defined in the middle panel. The variable *Ownership* is the share of either individual (Columns 1-3) or institutional investors (Columns 4-6) among all investors owning at least a share of total equity, as defined in the middle panel. Institutional investors include the largest financial investors in Table 2.1, namely, banks, mutual funds, and insurance firms. The variable *Ownership* is standardized. The AGM variable is an indicator variable taking value one if the firm has an AGM before April 15, 2020, and zero otherwise. All columns include industry- and state-fixed effects. Standard errors are clustered by industry.

Table 2.3: Correlation of donations of financial shareholders' and their portfolios

	Spearman Correlations		
Minimum Equity Share Considered	Simple Average	Weighted Average	Weighted Avg. × AGM
	[p-values]	[p-values]	[p-values]
(1)	(2)	(3)	(4)
0%	0.442	-0.062	-0.211
(Avg. N = 222)	[0.007]	[0.721]	[0.238]
1%	0.064	0.079	-0.093
(Avg. N = 100)	[0.751]	[0.696]	[0.705]
2%	-0.230	0.077	-0.439
(Avg. N = 57)	[0.280]	[0.721]	[0.089]
3%	-0.105	0.180	-0.617
(Avg. N = 48)	[0.643]	[0.423]	[0.077]
4%	-0.112	0.060	-0.878
(Avg. N = 42)	[0.630]	[0.795]	[0.021]
5%	0.124	0.275	-0.289
(Avg. N = 35)	[0.637]	[0.285]	[0.638]

Note: This table shows a negative correlation between large institutional investors such as financial firms in the S&P 500 Index and the firms in their portfolio that had their AGMs before April 15, 2020. The negative correlation indicates that financial investors opposed COVID-19-related donations in their footprints. The table computes the Spearman correlation between whether a financial firm donates and the share of donations at the firms in its portfolio. In each row, we vary the minimum share % that a firm must have in another firm to be considered an investment according to the percentages reported in the first column. Column 1 also reports the average number of S&P500 firms in the portfolio of a financial investor in parenthesis. Column 2 computes the total donations of the firms that financial firm i has invested in using simple averages (i.e., $N^{-1} \times \sum_j \mathbb{I}_{[\text{firm } j \text{ donated}]} \times \mathbb{I}_{[i\text{'s share in } j \text{ is greater than } x\%]}$, where N is the number of investments of firm i), Column 3 computes weighted average with weights equal to the equity shares (i.e., $\sum_j share_{ij} \times \mathbb{I}_{[\text{firm } j \text{ donated}]} \times \mathbb{I}_{[i\text{'s share in } j \text{ is greater than } x\%]}$), and column 4 considers only investments that got an AGM in the period under consideration (i.e., $\sum_j share_{ij} \times \mathbb{I}_{[\text{firm } j \text{ donated}]} \times \mathbb{I}_{[i\text{'s share in } j \text{ is greater than } x\%]} \times \mathbb{I}_{[j \text{ has an AGM}]}$). p-values testing whether the Spearman correlation is equal to zero are reported in square brackets.

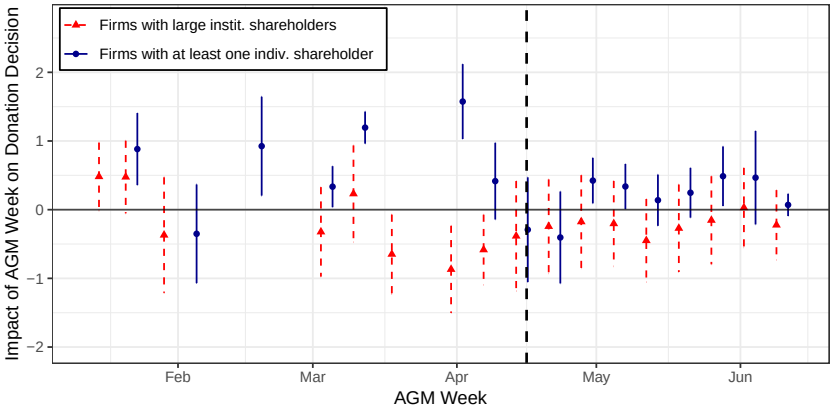
Table 2.4: Shareholders' influence on the decision to exit the Russian market

	Exited Russia in the Frist Month of Conflict (0/1)					
	(1)	(2)	(3)	(4)	(5)	(6)
AGM	−0.067	−0.080	−0.094	0.144	0.035	0.043
	(0.090)	(0.087)	(0.090)	(0.115)	(0.116)	(0.111)
Above Median Blockholding	−0.547***	−0.542***	−0.428***	0.116	0.070	0.148
	(0.181)	(0.145)	(0.128)	(0.132)	(0.134)	(0.137)
AGM × *Above Median Blockholding*	0.705***	0.316	0.263	−0.341**	−0.152	−0.188
	(0.254)	(0.244)	(0.175)	(0.165)	(0.160)	(0.159)
Above Median Blockholding (0/1) defined for:	Individual			Institutional		
Threshold to be considered a blockholder:	>10%	>5%	>2%	>10%	>5%	>2%
Controls	✓	✓	✓	✓	✓	✓
Sector fixed effects	✓	✓	✓	✓	✓	✓
N	138	138	138	138	138	138
Adjusted R-squared	0.2762	0.2923	0.2879	0.2642	0.2320	0.2372

* − $p < 0.1$; ** − $p < 0.05$; *** − $p < 0.01$.

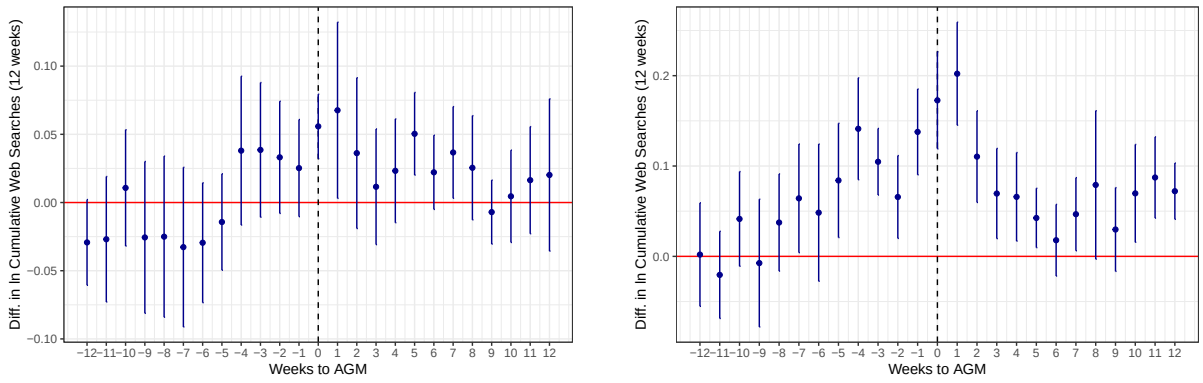
Note: The table presents the coefficients from OLS regressions of an indicator that is one if firm f has exited Russia by March 23, 2022, and zero otherwise on covariates. The regressions only exploit cross-section variation across firms at March 23, 2022. Italicized variables are defined in the middle panel. *Above Median Blockholding* is one if firm f has more blockholders of the reference category than the median S&P 500 firm and zero otherwise. The reference category and the blockholding thresholds are defined in the middle panel. Control variables include the share of revenues that come from activities in the US and Canada, the exposure to Russia, brokers' recommendations, CEO age, and net income. Market capitalization, revenues, and net income are highly correlated; controlling for any of these two variables instead of net income does not change the results qualitatively. For models where individual investors are the reference category (Columns 1 to 3), we also include a dummy equal to 1 for above-median institutional ownership. This variable is necessary to control whether institutional investors are heavily invested in a firm, as this channel could reduce the voice of individual and family shareholders. This variable would have been unnecessary if we could have exploited firm-fixed effects. All columns include sector-fixed effects. Robust standard errors in parenthesis.

Figure 2.1: Shareholders' influence on donations by AGM week



Note: The figure plots the estimated coefficients of an event study regressing whether a firm donated between January and April 2020 on dummies, indicating whether the firm held an AGM in the weeks between January 15 and June 15, 2020. The reference period is the week of June 15, 2020. Coefficients shown in circles are estimated using a sample of firms with at least one individual shareholder with at least 0.1% shares, and the triangles are from a sample of firms whose institutional blockholding (shareholders owning at least 5% a firm's equity as of December 2019) is greater than the median at S&P 500 firms. Standard errors are clustered by industry; vertical bars denote 95% confidence intervals. The vertical dashed line is on April 15, 2020, 90 days after the first US covid case.

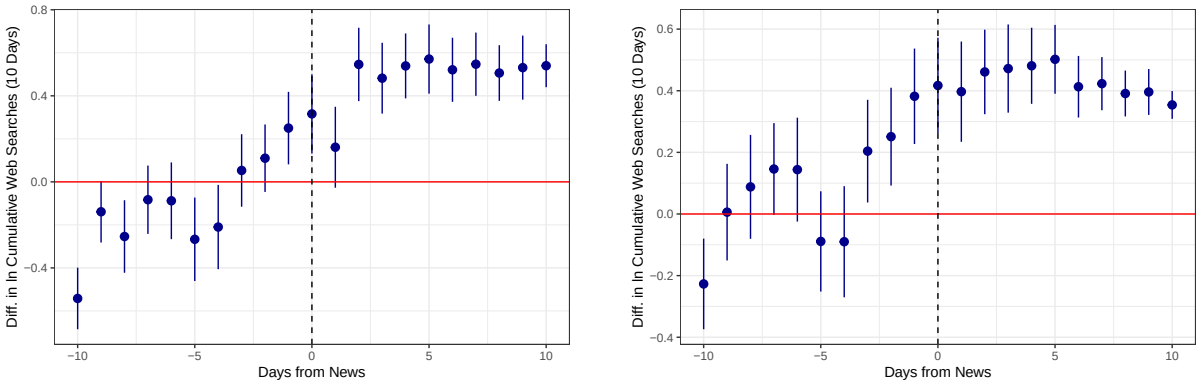
Figure 2.2: The gap in Google Trends of individual and institutional shareholders around an AGM



(a) All shareholders (b) Shareholders with +5% shares

Note: Both panels report coefficient estimates from Equation 2.4, which reports the (log) cumulative Google Trends score (twelve-week window) of shareholders' names over dummy variables describing a twelve-week window around a firms' AGM and the interaction of these dummies with an indicator function that is equal to one if the concerned shareholder is an individual or family shareholder and zero otherwise. The panels only report these interaction terms. Panel b) includes only shareholders with more than 5% shares. The vertical bars indicate 95% confidence intervals using clustered standard errors by firms and shareholder types (bank, company, individual, financial company, government, hedge fund, insurance, mutual fund, self-ownership).

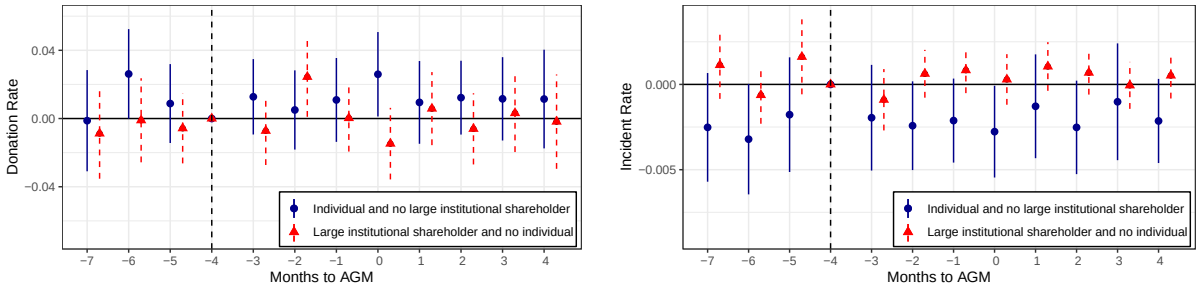
Figure 2.3: The gap in Google Trends of individual and institutional shareholders



(a) Shareholders with +1% shares (b) Shareholders with +5% shares

Note: Both panels report coefficient estimates from Equation 2.5, which reports the (log) cumulative Google Trends score (ten-day window) of shareholders' names over dummy variables describing a ten window around a firms' donation dates and the interaction of these dummies with an indicator function that is equal to one if the concerned shareholder is an individual or family shareholder and zero otherwise. The panels only report these interaction terms. Panel a (Panel b) includes only shareholders with more than 1% (5%) shares. The vertical bars indicate 95% confidence intervals using clustered standard errors by firms and shareholder types (bank, company, individual, financial company, government, hedge fund, insurance, mutual fund, self-ownership).

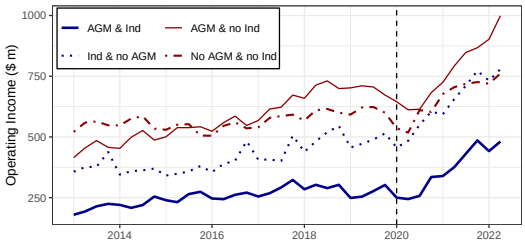
Figure 2.4: Shareholders' influence on firms' prosociality during AGMs



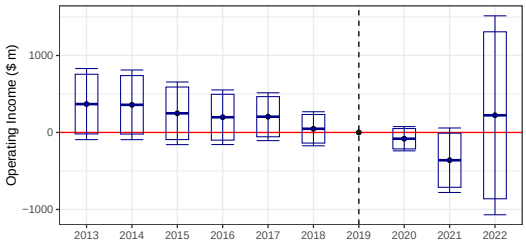
(a) Donations (b) Social ("S") incidents

Note: Panel a (b) reports coefficient estimates from the event study of an indicator for whether a firm has at least a donation event (a social incident) in a given month on either a dummy that is equal to one if the firm has at least one institutional blockholder (10%) and no individual shareholder (red triangles), or a dummy equal to one if a firm has at least one individual shareholder and no institutional blockholder with at least at 10% share (blue circles). The regressions include firm-by-year, month-by-year-by-state, and month-by-year-by-industry fixed effects. Standard errors are clustered at the firm level.

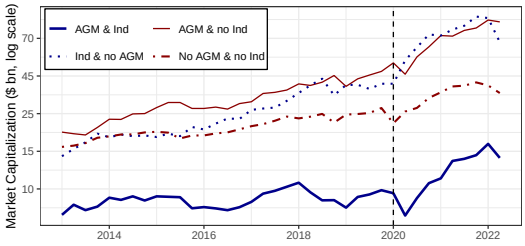
Figure 2.5: Documenting rents: covid case



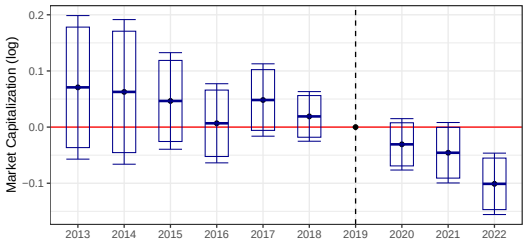
(a) Operating income (quarterly data)



(b) Operating income - event study



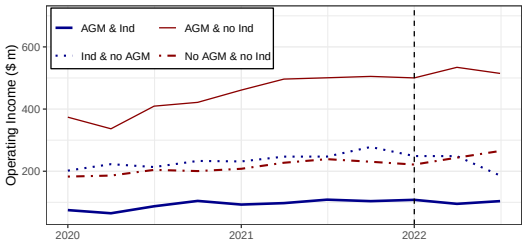
(c) Market cap (quarterly data)



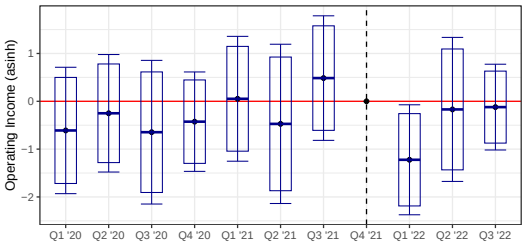
(d) Market cap (log) - event study

Note: Panels (a) and (c) plot the operating income and the market cap (in logs) for firms with and without an AGM between January 15 and April 15, 2020, and at least an individual shareholder with a 5% shares. Panels (b) and (d) plot the estimated coefficients from (2.9), where the coefficients of interest are the interaction between time dummies, a dummy equal to one if the firm holds an AGM between January 15 and April 15, 2020, and the share of individual shareholders with at least a 5% share. The regressions include controls and firm, year, and year-by-industry fixed effects. Standard errors are clustered at the industry and state levels. Error bars (boxes) report the 95% (90%) CI. Vertical dashed lines indicate the two events.

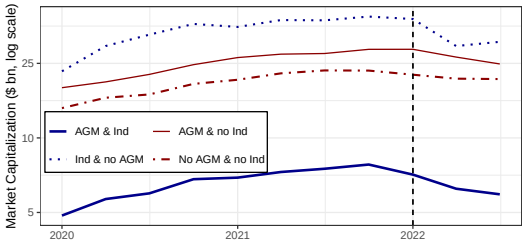
Figure 2.6: Documenting rents: Russian invasion of Ukraine



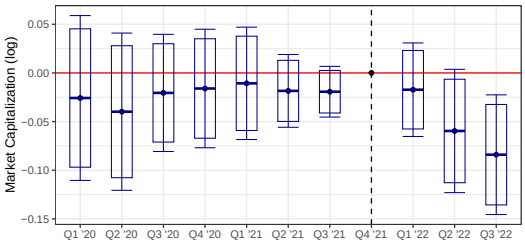
(a) Operating income



(b) Operating income - event study



(c) Market cap



(d) Market cap (log) - event study

Note: Panels (a) and (c) plot the operating income and the market cap (in logs) for firms with and without an AGM between February 24 and May 24, 2022, and at least an individual shareholder with a 5% shares. Panels (b) and (d) plot the estimated coefficients from (2.9), where the coefficients of interest are the interaction between time dummies, a dummy equal to one if the firm holds an AGM between February 24 and May 24, 2022, and the share of individual shareholders with at least a 5% share. The regressions include controls, firm, time, and time-by-industry-fixed effects. Standard errors are clustered at the industry and state levels. Error bars (boxes) report the 95% (90%) CI. Vertical dashed lines indicate the two events.

Appendix to Chapter 2

2.A Omitted Tables

Table 2.A1: The impact of institutional blockholders on covid donations

	Whether Firm f has made a Donation (0/1)								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Ownership	−0.030	−0.018	0.100***	−0.026	−0.038	−0.105***	0.058***	0.069***	0.018
	(0.020)	(0.017)	(0.025)	(0.016)	(0.025)	(0.020)	(0.012)	(0.010)	(0.030)
AGM	0.094	0.077	0.089	0.082	0.093	0.090	0.099	0.086	0.082
	(0.090)	(0.098)	(0.098)	(0.097)	(0.102)	(0.103)	(0.098)	(0.095)	(0.111)
Ownership × AGM	−0.073**	−0.020	−0.049	−0.030	−0.002	0.083**	−0.142***	−0.040	−0.049
	(0.030)	(0.062)	(0.046)	(0.043)	(0.035)	(0.030)	(0.018)	(0.059)	(0.079)
Constant	0.033	0.038	0.049	0.042	0.033	−0.002	0.057	−0.004	0.069
	(0.071)	(0.064)	(0.067)	(0.075)	(0.078)	(0.035)	(0.065)	(0.017)	(0.072)
Ownership is defined as:	Banks			Mutual Funds			Insurance		
Ownership is the shares of shareholders owning:	>10%	>5%	(0%, 2%)	>10%	>5%	(0%, 2%)	>10%	>5%	(0%, 2%)
Industry fixed effects	✓	✓	✓	✓	✓	✓	✓	✓	✓
State fixed effects	✓	✓	✓	✓	✓	✓	✓	✓	✓
N	433	433	433	433	433	433	433	433	433
Adjusted R-squared	0.1638	0.1565	0.1909	0.1575	0.1606	0.1921	0.1716	0.1696	0.1559

* − $p < 0.1$; ** − $p < 0.05$; *** − $p < 0.01$.

Note: This table zooms in on which institutional blockholders impacted covid-related donations the most. The table presents the coefficients from OLS regressions of an indicator variable that is one if firm f has donated by April 15, 2020, on covariates. Italicized variables are defined in the middle panel. The variable *Ownership* is the share of institutional investors (of the reference category defined in the middle panel) among all investors owning at least a share of total equity as defined in the middle panel. The variable *Ownership* is standardized. The AGM variable is an indicator variable taking value one if the firm has an AGM before April 15, 2020, and zero otherwise. All columns include industry- and state-fixed effects. Standard errors are clustered by industry.

Table 2.A2: Differential increase of Google Trend scores to individual over institutional investors around a donation announcement

	Google Trends Scores		(log) Comulative Google Web Searches Over					
	Daily		14 days		10 days		7 days	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Indiv. Sh.holder × 10 Days Before	−8.701***	−11.095***	−0.259***	−0.102	−0.542***	−0.227**	−0.337***	−0.132
	(1.617)	(2.884)	(0.079)	(0.072)	(0.073)	(0.075)	(0.058)	(0.072)
Indiv. Sh.holder × 9 Days Before	−11.347***	−14.754***	−0.195**	−0.018	−0.139*	0.006	−0.396***	−0.164*
	(0.910)	(1.781)	(0.084)	(0.074)	(0.073)	(0.080)	(0.064)	(0.077)
Indiv. Sh.holder × 8 Days Before	−8.722***	−12.710***	−0.131	0.044	−0.254**	0.088	−0.414***	0.004
	(1.276)	(3.061)	(0.087)	(0.087)	(0.086)	(0.086)	(0.078)	(0.085)
Indiv. Sh.holder × 7 Days Before	−11.431***	−16.198**	0.127	0.361***	−0.083	0.146*	−0.598***	0.033
	(1.755)	(4.901)	(0.080)	(0.080)	(0.081)	(0.076)	(0.081)	(0.081)
Indiv. Sh.holder × 6 Days Before	−5.798**	−8.352	0.149	0.383***	−0.088	0.144	−0.053	0.271**
	(2.581)	(5.907)	(0.087)	(0.086)	(0.091)	(0.086)	(0.099)	(0.098)
Indiv. Sh.holder × 5 Days Before	−2.846	−3.702	−0.033	0.171*	−0.267**	−0.089	−0.336***	−0.036
	(2.358)	(4.651)	(0.087)	(0.080)	(0.099)	(0.083)	(0.101)	(0.087)
Indiv. Sh.holder × 4 Days Before	−4.770*	−5.242	0.030	0.212**	−0.210*	−0.090	−0.135	−0.026
	(2.373)	(5.523)	(0.094)	(0.084)	(0.100)	(0.092)	(0.096)	(0.086)
Indiv. Sh.holder × 3 Days Before	−9.395***	−11.464**	0.091	0.231**	0.053	0.204**	−0.170	−0.056
	(1.975)	(4.360)	(0.096)	(0.090)	(0.086)	(0.085)	(0.099)	(0.083)
Indiv. Sh.holder × 2 Days Before	−7.173***	−8.182	0.242**	0.308***	0.110	0.251**	−0.051	0.073
	(1.811)	(4.527)	(0.093)	(0.082)	(0.080)	(0.081)	(0.101)	(0.085)
Indiv. Sh.holder × 1 Day Before	−5.140**	−5.507	0.289**	0.330***	0.250**	0.382***	0.085	0.152
	(2.220)	(5.913)	(0.092)	(0.074)	(0.086)	(0.079)	(0.099)	(0.086)
Indiv. Sh.holder × News Day	6.610*	2.246	0.334***	0.324***	0.316***	0.417***	0.400***	0.431***
	(3.522)	(6.770)	(0.088)	(0.065)	(0.094)	(0.079)	(0.074)	(0.077)
Indiv. Sh.holder × 1 Day After	−6.287**	−9.775*	0.306***	0.307***	0.161	0.397***	0.209**	0.388***
	(2.493)	(4.995)	(0.086)	(0.062)	(0.096)	(0.083)	(0.076)	(0.072)
Indiv. Sh.holder × 2 Days After	0.480	−2.515	0.384***	0.298***	0.546***	0.461***	0.384***	0.499***
	(2.234)	(3.410)	(0.074)	(0.055)	(0.087)	(0.070)	(0.074)	(0.073)
Indiv. Sh.holder × 3 Days After	−0.345	−0.037	0.385***	0.312***	0.482***	0.472***	0.220**	0.566***
	(1.806)	(2.785)	(0.076)	(0.046)	(0.084)	(0.073)	(0.087)	(0.082)
Indiv. Sh.holder × 4 Days After	3.035	3.911	0.404***	0.330***	0.539***	0.481***	0.446***	0.619***
	(1.742)	(2.211)	(0.074)	(0.042)	(0.077)	(0.063)	(0.076)	(0.085)
Indiv. Sh.holder × 5 Days After	0.739	−1.051	0.402***	0.290***	0.571***	0.502***	0.747***	0.630***
	(1.404)	(3.061)	(0.084)	(0.039)	(0.082)	(0.057)	(0.077)	(0.080)
Indiv. Sh.holder × 6 Days After	2.055	−0.048	0.419***	0.264***	0.521***	0.413***	0.683***	0.595***
	(2.192)	(3.311)	(0.080)	(0.038)	(0.076)	(0.051)	(0.074)	(0.073)
Indiv. Sh.holder × 7 Days After	−2.397	−4.423	0.404***	0.253***	0.547***	0.423***	0.693***	0.574***
	(1.735)	(2.759)	(0.074)	(0.034)	(0.075)	(0.044)	(0.069)	(0.059)
Indiv. Sh.holder × 8 Days After	−1.216	−2.355	0.375***	0.212***	0.506***	0.391***	0.688***	0.608***
	(2.281)	(3.572)	(0.081)	(0.037)	(0.066)	(0.038)	(0.072)	(0.059)
Indiv. Sh.holder × 9 Days After	6.062**	6.669**	0.498***	0.317***	0.531***	0.396***	0.689***	0.571***
	(2.062)	(2.536)	(0.069)	(0.031)	(0.076)	(0.038)	(0.062)	(0.052)
Indiv. Sh.holder × 10 Days After	7.752***	7.812***	0.377***	0.142***	0.540***	0.354***	0.697***	0.529***
	(1.403)	(1.617)	(0.067)	(0.034)	(0.051)	(0.023)	(0.049)	(0.034)
Consider only shareholders holding:	> 1%	> 5%	> 1%	> 5%	> 1%	> 5%	> 1%	> 5%
Time fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
Firm fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
Shareholder fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
N	397,893	125,772	350,276	110,504	365,106	115,206	376,035	118,728
Adjusted R-squared	0.6328	0.6609	0.7695	0.8009	0.7728	0.7898	0.7801	0.7880

$^{*} - p < 0.1$; $^{**} - p < 0.05$; $^{***} - p < 0.01$.

Note: This table finds that Google Trends scores are substantially higher for individual shareholders in the days after their firms pledge a donation. The table reports the OLS regression of Equation 2.5; the dependent variable is either the number of daily Google Trends scores (Columns 1 and 2) or the (log) cumulative Google Trends scores (Columns 3 to 8) of shareholder i's name owning shares in firm f on time dummies in a ten-day window around the date when firm f donated. The regression also includes the interaction of these dummy variables with an indicator that is one if shareholder i is an individual or family shareholder and zero otherwise. Only the interactions of the time dummies with the Individual Shareholder dummy are reported due to space constraints. All columns include firm-, shareholder-, and day-fixed effects. The dataset starts on January 15, 2020, and ends on April 15, 2020. Standard errors are clustered by firm-by-shareholder type (bank, company, individual, financial company, government, hedge fund, insurance, mutual fund, self-control) and presented in parenthesis.

Table 2.A3: The impact of various class of blockholders on covid donations through covid cases and deaths

	Whether Firm f has Donated by Time t (0/1)											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel a. Using Cumulative Covid Cases												
Covid Rate	0.018*	0.018*	0.020*	0.019*	0.021*	0.016	0.018	0.015	0.018	0.021*	0.021*	0.020*
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Covid Rate × *Ownership*	0.009**	0.008**	−0.015**	−0.008	−0.006	0.028***	−0.021*	−0.027**	−0.019*	0.002	−0.000	0.010
	(0.005)	(0.003)	(0.008)	(0.012)	(0.009)	(0.008)	(0.012)	(0.011)	(0.010)	(0.005)	(0.007)	(0.010)
Covid Rate × AGM	0.033	0.037	0.011	−0.023	0.008	0.043	−0.055	−0.040	0.000	0.063*	0.042	0.137
	(0.039)	(0.039)	(0.038)	(0.040)	(0.062)	(0.083)	(0.038)	(0.041)	(0.066)	(0.037)	(0.030)	(0.115)
Covid Rate × *Ownership* × AGM	0.127***	0.143***	0.042	−0.104***	0.007	0.002	−0.264***	−0.118***	0.034	−0.019***	−0.017	0.111
	(0.016)	(0.020)	(0.101)	(0.024)	(0.057)	(0.057)	(0.026)	(0.045)	(0.060)	(0.007)	(0.013)	(0.096)
Covid Rate is defined as:	Cumulative cases			Cumulative cases			Cumulative cases			Cumulative cases		
Reference shareholder category for *Ownership*:	Individual and family			Banks			Mutual Funds			Insurance		
Ownership is the shares of shareholders owning:	>10%	>5%	(0%, 2%)	>10%	>5%	(0%, 2%)	>10%	>5%	(0%, 2%)	>10%	>5%	(0%, 2%)
Adjusted R-squared	0.5017	0.5019	0.5008	0.5011	0.4997	0.5051	0.5008	0.5025	0.5019	0.5011	0.5001	0.5014
Panel b. Using Comulative Covid Deaths												
Covid Rate	0.016*	0.016*	0.017*	0.017*	0.018*	0.014	0.016*	0.014	0.015	0.018*	0.018**	0.017*
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Covid Rate × *Ownership*	0.007*	0.007**	− 0.013*	−0.006	−0.004	0.023***	−0.013	−0.020*	−0.014	0.001	−0.002	0.008
	(0.004)	(0.003)	(0.007)	(0.010)	(0.008)	(0.007)	(0.013)	(0.012)	(0.009)	(0.004)	(0.006)	(0.009)
Covid Rate × AGM	−0.060	0.068*	0.015	−0.081**	0.028	−0.035	−0.154***	−0.128**	−0.052	0.053***	0.041**	0.095
	(0.040)	(0.041)	(0.034)	(0.040)	(0.080)	(0.074)	(0.038)	(0.051)	(0.048)	(0.020)	(0.018)	(0.179)
Covid Rate × *Ownership* × AGM	0.308***	0.340***	0.123	−0.234***	0.028	−0.055	−0.649***	−0.317***	0.086*	−0.015***	−0.018**	0.073
	(0.053)	(0.070)	(0.160)	(0.042)	(0.062)	(0.051)	(0.047)	(0.092)	(0.048)	(0.005)	(0.008)	(0.148)
Covid Rate is defined as:	Cumulative deaths			Cumulative deaths			Cumulative deaths			Cumulative deaths		
Reference shareholder category for *Ownership*:	Individual and family			Banks			Mutual Funds			Insurance		
Ownership is the shares of shareholders owning:	>10%	>5%	(0%, 2%)	>10%	>5%	(0%, 2%)	>10%	>5%	(0%, 2%)	>10%	>5%	(0%, 2%)
Adjusted R-squared	0.5005	0.5005	0.5001	0.5003	0.4991	0.5028	0.4996	0.5008	0.5008	0.5001	0.4998	0.4996
Time fixed effects	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Firm fixed effects	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
N	36,805	36,805	36,805	36,805	36,805	36,805	36,805	36,805	36,805	36,805	36,805	36,805

* − $p < 0.1$; ** − $p < 0.05$; *** − $p < 0.01$.

Note: The table reports the OLS regressions based on Equation 2.6 where the dependent variable is an indicator that is one if firm f has donated by day t and zero otherwise on covariates. The table has three panels: Panel a. reports estimated coefficients when *Covid Rate* are defined as cumulative covid cases at the headquarters state of firm f by time t, Panel b. reports the same coefficients for cumulative covid deaths, and the bottom panel indicates the used fixed effects and the number of observations in each column. Italicized variables are defined in the middle panel. The evidence in this table suggests that institutional blockholders negatively impacted covid donations using covid cases as a proxy for the salience of the pandemic on the media. The variable *Ownership* varies across columns based as the share of a certain class of investors owning at least a given share of total equity (greater than 10%, greater than 5%, or between 0 and 2%). The AGM variable is an indicator variable taking value one if the firm has an AGM before April 15, 2020, and zero otherwise. All columns include day- and firm-fixed effects. The interaction *Ownership* × AGM and the direct effect of the variables *Ownership* and AGM are accounted for by the firm-fixed effects. The dataset starts on January 15, 2020, and ends on April 15, 2020. Standard errors are clustered by firm and presented in parenthesis.

Table 2.A4: The impact of covid exposure at branches on donations

	Whether Firm f has Donated by Time t (0/1)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Exposure at branches	0.007	0.009	0.012	0.014	0.008	0.008	0.010	0.011
	(0.017)	(0.013)	(0.012)	(0.012)	(0.015)	(0.011)	(0.010)	(0.010)
Exposure at branches × Number of branches (ln)	0.003				0.001			
	(0.005)				(0.005)			
Exposure at branches × *More than x branches*		0.024	0.039	0.020		0.018	0.039	0.016
		(0.024)	(0.028)	(0.045)		(0.024)	(0.029)	(0.050)
Exposure at branches is defined as:	Cumulative cases				Cumulative deaths			
More than x branches (0/1) is 1 if the firm has more branches than the x quantile:		50%	75%	90%		50%	75%	90%
Time fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
Firm fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
N	33,490	37,570	37,570	37,570	33,490	37,570	37,570	37,570
Adjusted R-squared	0.4979	0.4967	0.4969	0.4958	0.4978	0.4961	0.4965	0.4956

$^{*} - p < 0.1$; $^{**} - p < 0.05$; $^{***} - p < 0.01$.

Note: This table finds that consumers were not a driver of covid-related donations because covid exposure in the states where firms had their branches does not correlat with donations rates across firms. The table presents the coefficients from OLS regressions based on Equation 2.7 based on an indicator variable that is one if firm f has donated by day t and zero otherwise on covariates. Italicized variables are defined in the middle panel. Columns 1 to 4 use cumulative covid cases at the headquarters state, and Columns 5 to 8 use cumulative covid deaths. The variable *Number of branches* in Columns 1 and 5 is in log. The remaining columns use a dummy variable (*More than x branches*) for whether the focal firm has more than the x-percentile than the distribution of brunches: this value is 40 branches in Columns 2 and 6, 170 branches in Columns 3 and 7, and 664 branches in Columns 4 and 8. Orbis data do not report branches for 15 firms, which are therefore omitted from the analysis. All columns include day- and firm-fixed effects. For this reason, the table does not report the direct effect of the *Number of Branches*, which does not vary over time and, thus, is captured by the firm-fixed effects. The dataset starts on January 15, 2020 and ends on April 15, 2020. Standard errors are clustered by firm and presented in parenthesis.

Table 2.A5: Abnormal and cumulative abnormal returns, using stock return forecasts based on data from the 60 days before a donation announcement

	Abnormal Returns	Comulative Abnormal Returns		
		7 days	10 days	14 days
	(1)	(2)	(3)	(4)
10 Days Before	−0.136	0.543	0.216	−0.771
	(0.302)	(0.789)	(0.806)	(0.768)
9 Days Before	−0.172	1.197	0.106	−0.734
	(0.365)	(0.889)	(0.868)	(0.837)
8 Days Before	0.168	1.219	0.879	−0.255
	(0.333)	(0.997)	(0.946)	(0.892)
7 Days Before	0.524	0.267	0.228	−0.568
	(0.352)	(1.078)	(0.982)	(0.981)
6 Days Before	−0.204	−0.208	−1.166	−1.555
	(0.478)	(1.070)	(1.010)	(1.070)
5 Days Before	−0.418	0.747	−0.944	−1.242
	(0.432)	(0.977)	(0.970)	(1.017)
4 Days Before	0.961**	0.786	−0.436	−1.138
	(0.407)	(0.951)	(0.972)	(1.036)
3 Days Before	0.761	−1.396	−1.149	−2.140*
	(0.464)	(1.051)	(1.045)	(1.129)
2 Days Before	−0.426	−2.204**	−2.674**	−3.544***
	(0.539)	(1.116)	(1.100)	(1.239)
1 Day Before	−0.702	−1.571	−2.381**	−3.226**
	(0.559)	(1.202)	(1.140)	(1.343)
Day of the Donation	−0.334	−1.054	−1.944*	−2.777*
	(0.544)	(1.286)	(1.110)	(1.485)
1 Day After	0.929	−1.453	−1.866*	−2.536*
	(0.598)	(1.113)	(1.042)	(1.414)
2 Days After	−1.036*	−2.201**	−3.404***	−3.799***
	(0.540)	(1.077)	(1.102)	(1.403)
3 Days After	−1.337**	−1.043	−2.046*	−2.444
	(0.547)	(1.055)	(1.117)	(1.488)
4 Days After	0.827	0.144	−0.108	−0.346
	(0.523)	(1.293)	(1.280)	(1.630)
5 Days After	0.046	−1.144	−1.132	−1.588
	(0.769)	(1.507)	(1.420)	(1.867)
6 Days After	0.606	0.171	−1.353	−1.470
	(0.755)	(1.345)	(1.418)	(1.670)
7 Days After	−0.717	−0.288	−1.733	−1.240
	(0.555)	(1.046)	(1.250)	(1.338)
8 Days After	−0.366	0.940	0.106	0.312
	(0.641)	(1.110)	(1.411)	(1.274)
9 Days After	0.063	0.790	1.578	1.540
	(0.525)	(0.979)	(1.134)	(1.112)
10 Days After	1.214	0.969	1.689	1.985
	(0.764)	(1.403)	(1.331)	(1.456)
Time fixed effects	✓	✓	✓	✓
Firm fixed effects	✓	✓	✓	✓
N	22,246	22,246	22,246	22,246
Adjusted R-squared	0.0331	0.1039	0.1401	0.1880

* − $p < 0.1$; ** − $p < 0.05$; *** − $p < 0.01$.

Note: This table reports the coefficients from an event study using the abnormal returns (ARs) and cumulative abnormal returns (CARs) around the day of the donation (model 2.4.4). ARs are computed as the difference between realized excess returns and the prediction of a one-factor model (the market factor), for which the stock's beta is computed over the last 60 days. The sample period goes from January 1 to April 15, 2020. All columns include firm and day-fixed effects. Standard errors are clustered by firm and are presented in parenthesis.

Table 2.A6: The impact of self-ownership on covid donations

	Whether Firm f has Donated by Time t (0/1)					
	(1)	(2)	(3)	(4)	(5)	(6)
Covid Rate	0.022**	0.019**	0.114***	0.100***	−0.003	−0.001
	(0.011)	(0.009)	(0.007)	(0.006)	(0.015)	(0.012)
Covid Rate × *Ownership*	−0.035	−0.034	−0.019	−0.016	0.010	−0.007
	(0.028)	(0.024)	(0.028)	(0.026)	(0.060)	(0.052)
Covid Rate × AGM	0.067*	0.057***	0.028	0.025	0.068	0.084
	(0.038)	(0.021)	(0.028)	(0.025)	(0.055)	(0.070)
Covid Rate × *Ownership* × AGM	−0.109**	−0.091***	−0.079	−0.075	−0.024	0.075
	(0.048)	(0.031)	(0.068)	(0.063)	(0.283)	(0.349)
Covid Rate is defined as:	Cases	Deaths	Cases	Deaths	Cases	Deaths
Ownership (0/1) is:	High self-ownership		High self-ownership		High self-ownership	
	At Headquarter		National Rates		At Branches	
Time fixed effects	✓	✓	✓	✓	✓	✓
Firm fixed effects	✓	✓	✓	✓	✓	✓
N	38,845	38,845	38,845	38,845	29,665	29,665
Adjusted R-squared	0.4958	0.4948	0.4927	0.4924	0.5007	0.5006

* − $p < 0.1$; ** − $p < 0.05$; *** − $p < 0.01$.

Note: This table finds that greater self-ownership shares negatively affect the probability that a firm donates. We use this variable as a proxy for managerial freedom. Thus, the table implies that managers did not favor donations. The table presents the coefficients from OLS regressions based on Equation 2.6 of an indicator variable that is one if firm f has donated by day t and zero otherwise on covariates. Italicized variables are defined in the middle panel. We vary the definition of *Covid Rate* across columns. Columns 1 and 2 measure covid at the headquarters state, Columns 3 and 4 measure covid at the national level, and Columns 5 and 6 measure covid at the state of the branches using the number of branches as weights. The last two columns restrict the data to firms with at least five branches. The variable *Ownership* is one if the share of equity owned by the firm itself is greater than its median value in the dataset and zero otherwise. The variable *Covid Rate* is standardized. The AGM variable is an indicator variable taking value one if the firm has an AGM before April 15, 2020, and zero otherwise. All columns include day- and firm-fixed effects. The interaction *Ownership* × AGM and the direct effect of the variables *Ownership* and AGM are accounted for by the firm-fixed effects. The dataset starts on January 15, 2020, and ends on April 15, 2020. Standard errors are clustered by firm and presented in parenthesis.

Table 2.A7: The impact of individuals blockholders on covid donations

	Whether Firm f has Donated by Time t (0/1)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Competitor Donating (0/1)	0.018*	0.017*	0.018**	0.017*	0.018*	0.018*	0.018**	0.018*
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Cum. Covid Rate	0.021	0.023*	0.050**	0.023*	0.018	0.020*	0.042**	0.020*
	(0.013)	(0.013)	(0.024)	(0.013)	(0.012)	(0.011)	(0.021)	(0.012)
AGM × *Cum. Covid Rate*	0.047	0.023	0.145**	0.008	0.062	0.023	0.159***	-0.019
	(0.053)	(0.052)	(0.068)	(0.052)	(0.054)	(0.048)	(0.049)	(0.036)
Ownership × *Cum. Covid Rate*	0.008**	-0.020**	-0.056	-0.003	0.007*	-0.017**	-0.046	-0.003
	(0.004)	(0.009)	(0.043)	(0.009)	(0.004)	(0.008)	(0.040)	(0.008)
AGM × *Ownership* × *Cum. Covid Rate*	0.133***	0.042	-0.310*	-0.047	0.264***	0.121	-0.379***	-0.082*
	(0.025)	(0.101)	(0.169)	(0.058)	(0.061)	(0.171)	(0.116)	(0.045)
Covid Rate is defined as:	Cumulative cases				Cumulative deaths			
Shareholder type is defined as:	Individual		Institutional		Individual		Institutional	
Ownership is the share of shareholders owning:	$> 5\%$	$(0\%, 2\%)$	$> 5\%$	$(0\%, 2\%)$	$> 5\%$	$(0\%, 2\%)$	$> 5\%$	$(0\%, 2\%)$
Time fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
Firm fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
N	43,300	43,300	43,300	43,300	43,300	43,300	43,300	43,300
Adjusted R-squared	0.5538	0.5537	0.5549	0.5526	0.5529	0.5530	0.5542	0.5525

* – $p < 0.1$; ** – $p < 0.05$; *** – $p < 0.01$.

Table 2.A8: The average cost shared by shareholders

	Crisis 1: Covid Pandemic						Crisis 2: Russian Invasion of Ukraine					
	Operating Income ($m)			Market Cap (ln)			Operating Income ($m)			Market Cap (ln)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
						Main Coefficients						
Ownership (≥ 10%) × Treat (0/1) × Post (0/1)	-13,014**			-4.09***			-308‡			-1.31*		
	(6,046)			(1.38)			(214)			(0.77)		
Ownership (≥ 5%) × Treat (0/1) × Post (0/1)		-7,644*			-3.36***			-319†			-1.086†	
		(4,431)			(1.09)			(199)			(0.661)	
Ownership (0/1) × Treat (0/1)			200			-0.1864*			-2.63			-0.0296
			(340)			(0.0963)			(37.89)			(0.0588)
						Direct Effects						
Ownership (≥ 10%) × Post (0/1)	6,731			1.995**			-35.4			0.528		
	(5,248)			(0.908)			(168.4)			(0.335)		
Ownership (≥ 5%) × Post (0/1)		3080			1.595**			-87.1			0.504*	
		(3,214)			(0.668)			(128.4)			(0.292)	
Ownership (0/1) × Post (0/1)			242			-0.00794			-6.77			0.0208
			(237)			(0.04712)			(21.51)			(0.0469)
Treat (0/1) × Post (0/1)	336	339	9.56	0.0917	0.1017	0.1938**	45.2	45.7	44.4	0.0998***	0.1036***	0.1030**
	(389)	(407)	(462.14)	(0.0741)	(0.0749)	(0.0925)	(31.3)	(32.0)	(38.5)	(0.0336)	(0.0339)	(0.0488)
Ownership is the Ownership of individuals:	≥ 10%	≥ 5%	1 if ≥ 5%	≥ 10%	≥ 5%	1 if ≥ 5%	≥ 10%	≥ 5%	1 if ≥ 5%	≥ 10%	≥ 5%	1 if ≥ 5%
Time fixed effects	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Firm fixed effects	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Industry-by-Time fixed effects	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
N	7,644	7,644	7,644	8,420	8,420	8,420	12,440	12,440	12,440	12,608	12,608	12,608
Adjusted R-squared	0.929	0.929	0.929	0.917	0.917	0.917	0.936	0.936	0.936	0.975	0.975	0.975

‡ − $p < 0.16$; † − $p < 0.12$; * − $p < 0.1$; ** − $p < 0.05$; *** − $p < 0.01$.

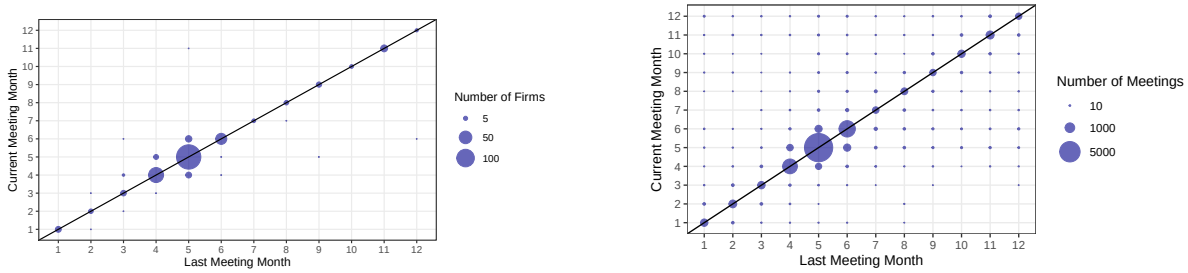
Note: This table presents the coefficients from the triple difference-in-differences analysis described in Section 2.5 for either the covid crisis (Columns 1 to 6) or the Russian invasion of Ukraine (Columns 7 to 12). The model is as follows:

$$y_{ft} = \beta_0\, Ownership_f \times \text{Treat}_f \times \text{Post}_t + \beta_1\, Ownership_f \times \text{Post}_t + \beta_2\, \text{Treat}_f \times \text{Post}_t + \mathbf{X}_{ft}\gamma + \alpha_f + \tau_t + \iota_{i(f)t} + \varepsilon_{ft},$$

where the dependent variable is defined in the header of each column. $Ownership_f$ varies across columns and can be either the share of individual investors with at least 10%, the share of individual investors with at least 5%, or a dummy variable that is one if the firm has at least one individual shareholder with a 5% share. In Columns 1 to 6 (7 to 12), $Treat_f = 1$ if firm f had an AGM between January 15, 2020, and April 15, 2020 (February 24, 2022, and May 24, 2022), and zero otherwise and $Post_t = 1$ from 2020 onwards (from the first quarter of 2022 onwards). Columns 1 to 6 use yearly data, while Columns 7 to 12 use quarterly data. Each column control for the past lagged total assets and fixed effects by firm, time, and industry by time. Operating income is winsorised at 1% and 99%. The standard errors are clustered by state and industry.

2.B Omitted Figures

Figure 2.B1: Stability of the AGM month over time

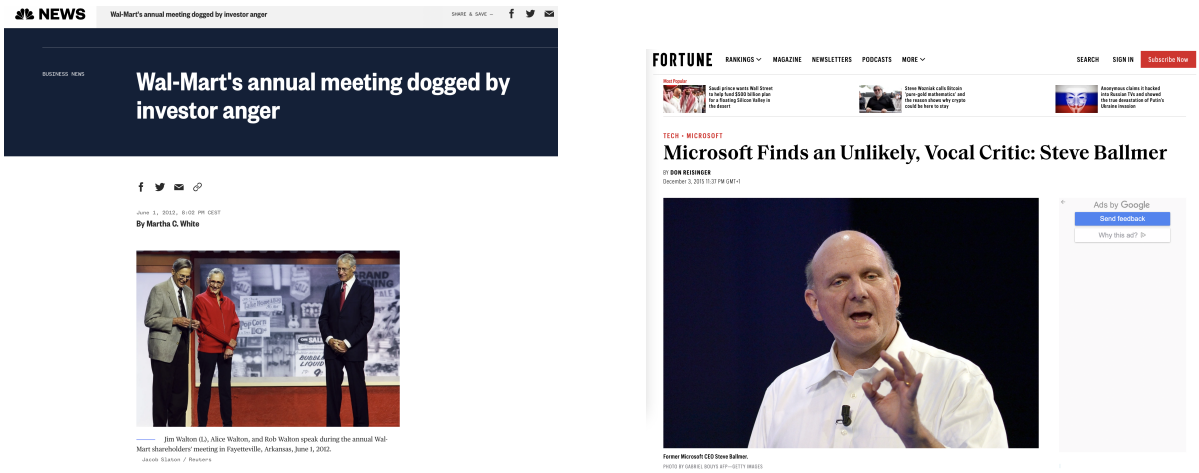


(a) AGM Months in 2019 and 2020

(b) AGM Months between 2012 and 2019

Note: Both panels count the occurrences of the AGM month over two adjacent years. A dot in position (2,3) means that at least one firm with an AGM in March of year t had an AGM in February of year $t-1$. The size of the blue dot refers to the number of firms. Dots on the diagonal solid line indicate firms that did not change AGM month over time. Panel (a) focuses on the first six months of 2020, while Panel (b) focuses on all years between 2012 and 2019. In the last case, observations are at the firm-by-year level as firms have more than one AGM.

Figure 2.B2: Examples of prominent shareholders featured on the media during AGMs

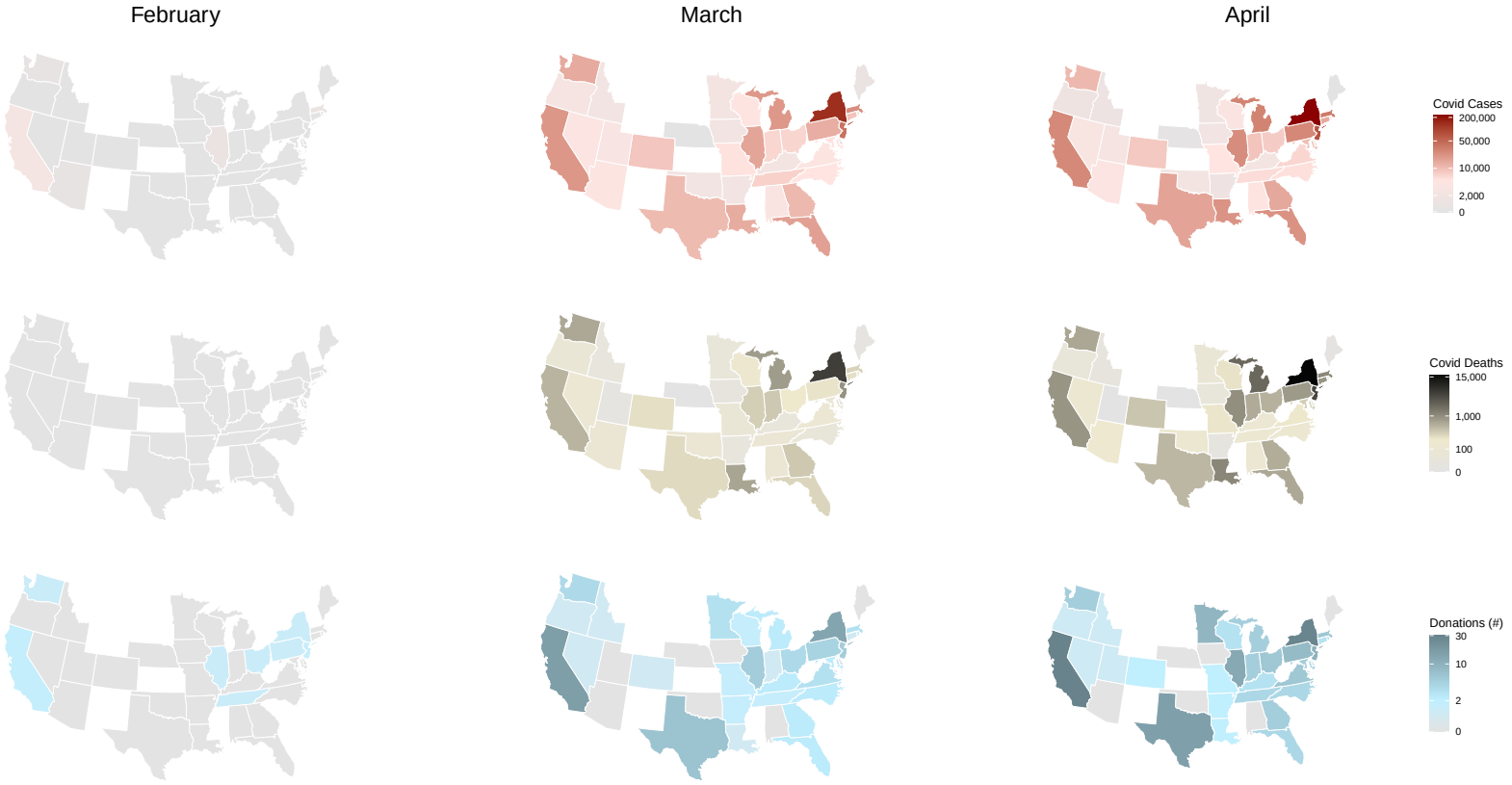


(a) Walton family members for Walmart

(b) Steve Ballmer for Microsoft

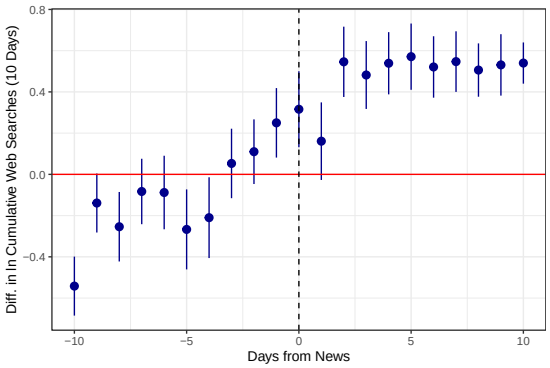
Note: The source for Panel a is `https://www.nbcnews.com/business/business-news/wal-marts-annual-meeting-dogged-investor-anger-flna808050`. The source for Panel b is `https://fortune.com/2015/12/03/microsoft-critic-steve-ballmer/`

Figure 2.B3: Covid cases, deaths, and corporate donations by US state and month

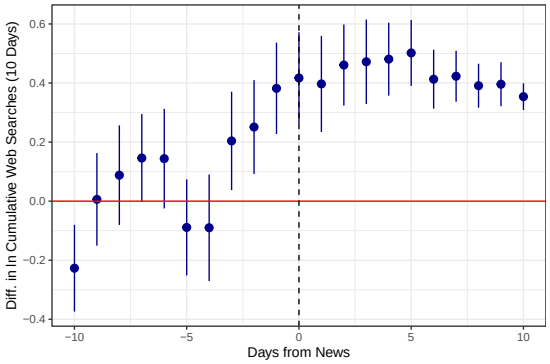


Note: The figure highlights the spatial and temporal correlation between the cumulative number of covid cases (first row), deaths (second row), and donations of S&P 500 companies (third row). Each column reports the breakdown for each variable across US states on February 29 (Column 1), March 31 (Column 2), and April 15 (Column 3), when our sample ends. States in white do not house S&P 500 firms. Covid rates come from Johns Hopkins University. Donation data are hand-collected using various online sources.

Figure 2.B4: Google Trends scores for individual and institutional blockholder



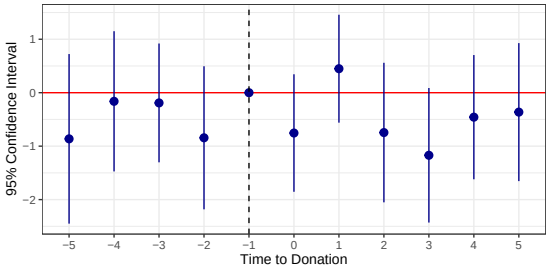
(a) Shareholders holding more than 1% of a firm's equity



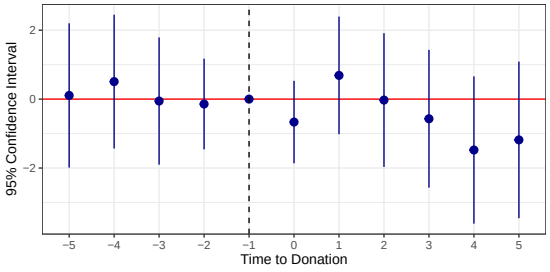
(b) Shareholders holding more than 5% of a firms's equity

Note: This figure presents results consistent with Figure 2.3 in the main text, but cumulating Google Trends scores over two weeks instead of 10 days. The panels show the difference in cumulative scores of individual and institutional shareholders around a donation event. The regression is detailed in Section 2.4.3. Appendix Table 2.A2 reports the coefficient estimates. Standard errors are clustered by firm-by-shareholder type (bank, company, individual, financial company, government, hedge fund, insurance, mutual fund, self-control) and presented in parenthesis.

Figure 2.B5: Abnormal and cumulative abnormal returns - event study



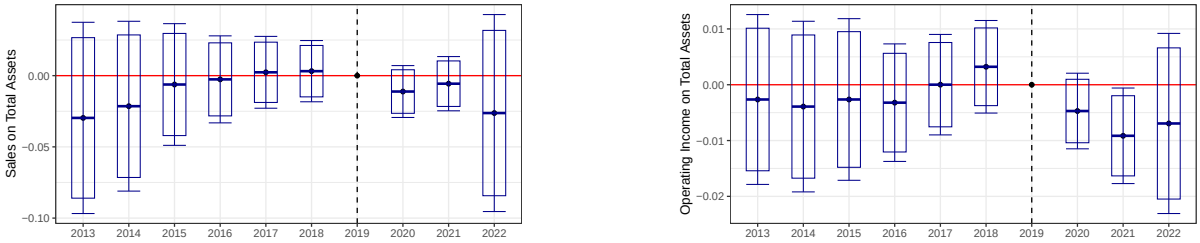
(a) Abnormal returns (AR)



(b) Cumulative AR over five days (CAR)

Note: This figure suggests that firms do not choose to donate to improve their performance on the stock market. Panel a plots abnormal returns (ARs) while Panel b plots cumulative abnormal returns (CARs) computed using the methodology outlined in Section 2.4.4. Date 0 is the date when the donation was made public. All coefficients are relative to the AR or CAR computed for the day before the donation event. We report the event study for a five-day window around the donation announcement. Appendix Table 2.A5 shows that the analysis is robust to various definitions of ARs and CARs and to various lengths of the event study interval.

Figure 2.B6: Sales or costs: What drove productivity down during the Covid crisis?

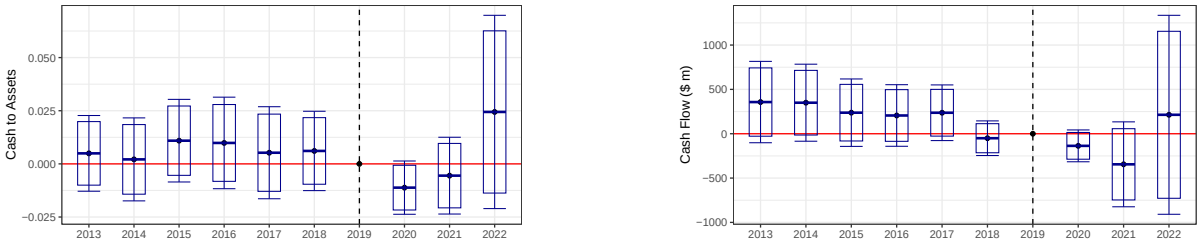


(a) Sales on total assets

(b) Operating Income on total assets

Note: The figure reports the estimated coefficients from an event study as in (2.9), with sales on total assets as the dependent variable in Panel (a) and operating income on total assets in Panel (b). We report only the estimated coefficients of interest – the interaction between the time dummies and a dummy equal to one if the firm has an AGM in the 90 days after the onset of the emergency and the share of individual shareholders with more than 5% equity shares. Each regression also includes controls and firm-, time-, and time-by-industry-fixed effects as described in Section 2.5. The dataset considers the largest 1,000 US-listed firms. Standard errors are clustered at the state and industry levels. Error bars (boxes) report the 95% (90%) CI. Vertical dashed lines indicate the time of the event.

Figure 2.B7: Cash imbalances due to shareholders' rent-extraction during covid

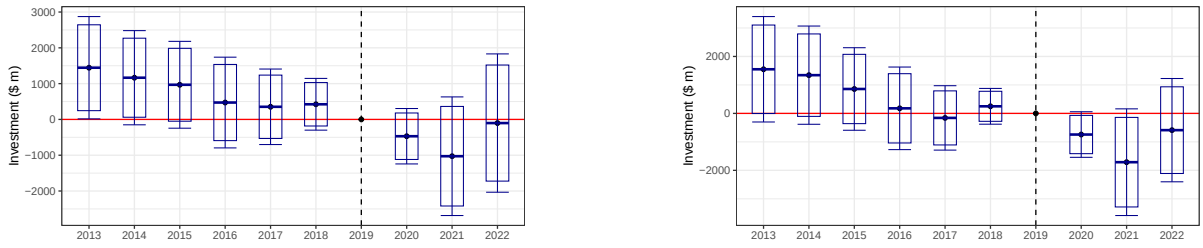


(a) Cash holdings on total assets

(b) Cash flows

Note: The figure reports the estimated coefficients from an event study as in (2.9), with cash holdings on total assets as the dependent variable in Panel (a) and cash flows on total assets in Panel (b). We report only the estimated coefficients of interest – the interaction between the time dummies and a dummy equal to one if the firm has an AGM in the 90 days after the onset of the emergency and the share of individual shareholders with more than 5% equity shares. Each regression also includes controls and firm-, time-, and time-by-industry-fixed effects as described in Section 2.5. The dataset considers the largest 1,000 US-listed firms. Standard errors are clustered at the state and industry levels. Error bars (boxes) report the 95% (90%) CI. Vertical dashed lines indicate the time of the event.

Figure 2.B8: Investments dropped at treated manufacturing firms

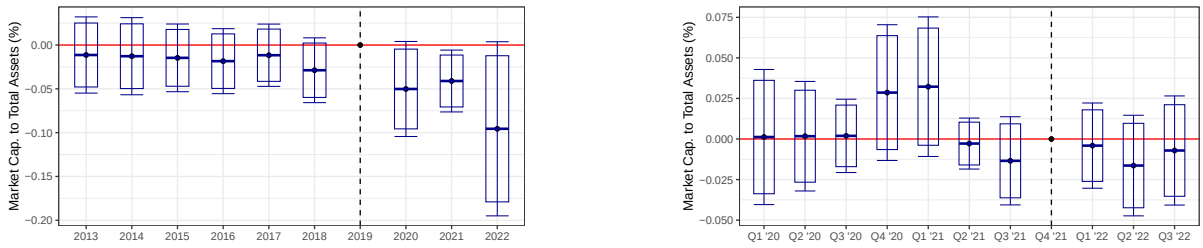


(a) All sectors

(b) Excluding service sectors

Note: The figure reports the estimated coefficients from an event study as in (2.9), with total invested capital as the dependent variable. Panel (a) shows the average effect in the whole sample (1,000 firms). Panel (b) excludes firms in service sectors (health care, financial, telecommunication services, utilities, real estate – 549 firms in total). We report only the estimated coefficients of interest – the interaction between the time dummies and a dummy equal to one if the firm has an AGM in the 90 days after the onset of the emergency and the share of individual shareholders with more than 5% equity shares. Each regression also includes controls and firm-, time- and time-by-industry-fixed effects as described in Section 2.5. The dataset considers the largest 1,000 US-listed firms. Standard errors are clustered at the state and industry levels. Error bars (boxes) report the 95% (90%) CI. Vertical dashed lines indicate the time of the event.

Figure 2.B9: The Equity to Asset ratio dropped for the Covid case only

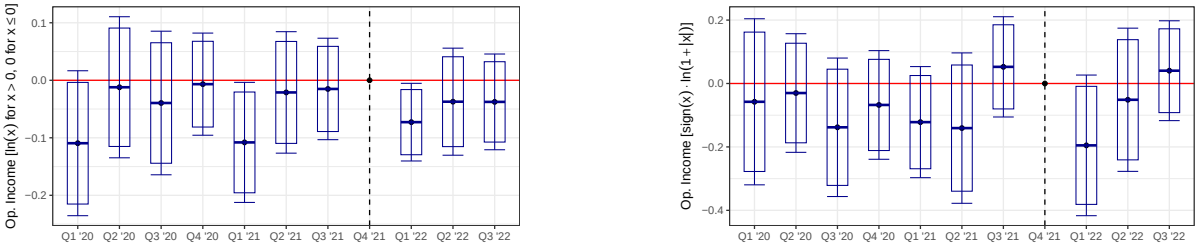


(a) Covid

(b) Russia-Ukraine

Note: The figure reports the estimated coefficients from an event study as in (2.9) with market capitalization on total assets as the dependent variable. Panels (a) and (b) focus on the covid and the Russia-Ukraine cases, respectively. We report only the estimated coefficients of interest – the interaction between the time dummies and a dummy equal to one if the firm has an AGM in the 90 days after the onset of the emergency and the share of individual shareholders with more than 5% equity shares. Each regression also includes controls and firm-, time- and time-by-industry-fixed effects as described in Section 2.5. The dataset in Panel (a) considers the largest 1,000 US-listed firms and that in Panel (b) considers the largest US-listed firm with a positive revenue share from Russia (1,153 firms). Standard errors are clustered at the state and industry levels. Error bars (boxes) report the 95% (90%) CI. Vertical dashed lines indicate the time of the event.

Figure 2.B10: Monotonic transformations of operating income – Russia-Ukraine



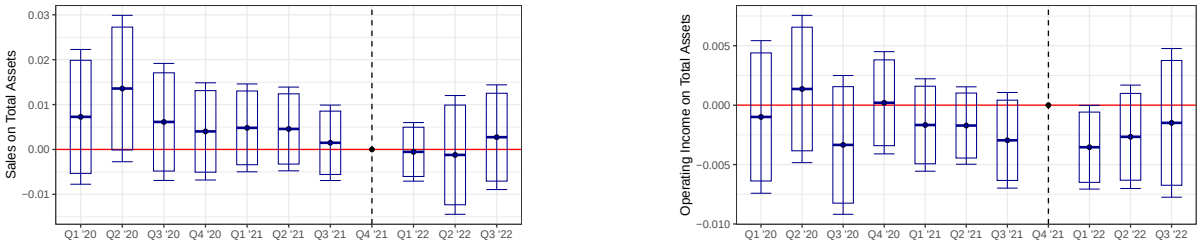
(a) ln(Op. In.) if OP. In. > 0, 0 otherwise

(b) $sign(\text{Op. In.}) \cdot \ln(1 + |\text{Op. In.}|)$

Note: The figure reports the estimated coefficients from an event study as in (2.9), with a monotonic transformation of operating income (OI) as the dependent variable. Panel (a) takes the log of OI for positive values of OI and 0 for values of OI less or equal to zero. Panel (b) takes $sign(OI) \cdot \ln(1+|OI|)$. We report only the estimated coefficients of interest – the interaction between the time dummies and a dummy equal to one if the firm has an AGM in the 90 days after the onset of the emergency and the share of individual shareholders with more than 5% equity shares. Each regression also includes controls and firm-, quarter-by-year- and quarter-by-year-by-industry-fixed effects as described in Section 2.5. As in Panel (b) of Figure 2.6 in the main text, the coefficient for Q1 2022 is statistically significant at 10% level in both panels. Its magnitude can be interpreted as a 7.4% (p-value = 0.036) drop compared to the average value of the transformed OI in Panel (a) and 6.5% (p-value = 0.086) for the transformation in Panel (b). The dataset considers the largest US-listed firms with a positive revenue share from Russia (1,153 firms). Standard errors are clustered at the state and industry levels. Error bars (boxes) report the 95% (90%) CI. Vertical dashed lines indicate the time of the event.

Figure 2.B11: Sales or costs: What drove productivity down in the Russia-Ukraine case?

Service sectors are excluded

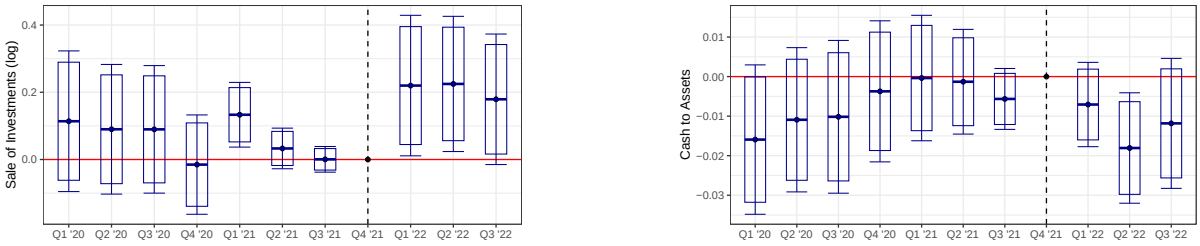


(a) Sales on total assets

(b) Operating income on total assets

Note: The figure reports the estimated coefficients from an event study as in (2.9), with sales on total assets as the dependent variable in Panel (a) and operating income on total assets in Panel (b). We exclude firms in non-manufacturing sectors like health care, financial, telecommunication services, utilities, and real estate. As a result, the number of firms is 511 and 512 in Panels (a) and (b), respectively. We report only the estimated coefficients of interest – the interaction between the time dummies and a dummy equal to one if the firm has an AGM in the 90 days after the onset of the emergency and the share of individual shareholders with more than 5% equity shares. Each regression also includes controls and firm-, quarter-by-year- and quarter-by-year-by-industry-fixed effects as described in Section 2.5. The dataset considers the largest US-listed firm with a positive revenue share from Russia (1,153 firms). Standard errors are clustered at the state and industry levels. Error bars (boxes) report the 95% (90%) CI. Vertical dashed lines indicate the time of the event.

Figure 2.B12: Rushing out of Russia: sales of investments and cash holdings

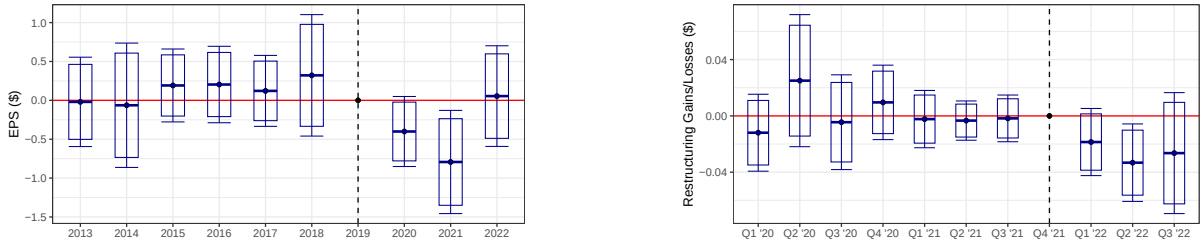


(a) Sales of investments

(b) Cash to Assets ratio

Note: The figure reports the estimated coefficients from an event study as in (2.9), with the sale of investments (log) and the ratio between cash holdings and total assets as dependent variables in Panels (a) and (b), respectively. We report only the estimated coefficients of interest – the interaction between the time dummies and a dummy equal to one if the firm has an AGM in the 90 days after the onset of the emergency and the share of individual shareholders with more than 5% equity shares. Each regression also includes controls and firm-, time- and time-by-industry-fixed effects as described in Section 2.5. The dataset considers the largest US-listed firm with a positive revenue share from Russia (1,153 firms). Standard errors are clustered at the state and industry levels. Error bars (boxes) report the 95% (90%) CI. Vertical dashed lines indicate the time of the event.

Figure 2.B13: The impact of shareholders' voice on earnings per share



(a) Earnings per share (EPS) - Covid case

(b) Restructuring costs basic EPS effect - Ukraine-Russia case

Note: The figure reports the estimated coefficients from an event study as in (2.9). The dependent variable is the EPS inclusive of the extraordinary items ($) in Panel (a) and the sum of all basic EPS effect items reported that correspond to restructuring costs in Panel (b), respectively. These costs include Chapter 11 reorganization costs and expenses, closing costs, exit costs, reductions in workforce, and relocation charges. Special item income/gains are positive an special item expenses/losses are negative. We report only the estimated coefficients of interest – interaction between the time dummies and a dummy equal to one if the firm has an AGM in the 90 days after the onset of the emergency and the share of individual shareholders with more than 5% equity shares. Each regression also includes controls and firm-, time- and time-by-industry-fixed effects as described in Section 2.5. The dataset in Panel (a) considers the largest 1,000 US-listed firms and that in Panel (b) considers the largest US-listed firm with a positive revenue share from Russia (1,153 firms). Standard errors are clustered at the state and industry levels. Error bars (boxes) report the 95% (90%) CI. Vertical dashed lines indicate the time of the event.

2.C Public Scrutiny Increases During AGM Periods

This section investigates the claim that a firm's AGM increases its media exposure and coverage of ESG-related events by showing that news coverage of NGO campaigns against a firm increases during AGM periods.

NGO reports data. We employ data from Sigwatch, a European consulting firm tracking and analyzing NGO campaigns globally (Hatte and Koenig, 2020). A campaign is defined as an event launched by an NGO against one or several companies on a given topic. The dataset indicates the date when a campaign has been made public on an NGO's website, the targeted company, its cause (e.g., "GMOs in food"), a measure of the sentiment ranging from −2 to +2, and the prominence of the firm in the campaign. We keep only campaigns targeting US-headquartered listed firms with a negative tone (sentiment < 0), where only one firm is mentioned, and the mention appears in the headline (prominence = 4). We are left with 1,036 NGO reports from January 2010 to December 2019. Figure 2.C1 shows the number of NGO campaigns annually.

News data. Firm-level news data come from Ravenpack. We keep only news with a relevance score of at least 75%. Due to our interest in AGMs, we consider only US-listed firms from 2010 to 2020 (4,676 firms) and aggregate the number of news by firm and week. The average number of weekly news for the firms in our sample is 12.7.

Analysis. Figure 2.C2 shows that news coverage grows during AGM periods for each year. To assess how the AGM period affects media exposure, we estimate:

$$\begin{aligned} \text{News}_{fw} = \beta_0 \text{NGO}_{fw} + \beta_1 \text{Proximity to AGM}_{fw} \\ + \beta_{treat} \text{NGO}_{fw} \times \text{Proximity to AGM}_{fw} + \alpha_f + \tau_w + \epsilon_{fw}, \end{aligned} \tag{2.C1}$$

where News_{fw} is the log number of news about firm f in week w plus one, NGO_{fw} is equal to one if a negative NGO report has been published about firm f during week w, and Proximity to AGM_{fw} is the inverse of one plus the distance (in weeks) to the nearest AGM. Therefore, for firm f in week w Proximity to AGM_{fw} is close to zero if firm f's yearly AGM is far away from week w and is one if, instead, its AGM is in week w and zero otherwise. The regression includes firm- and week-fixed effects. Table 2.C1 finds that firms receive more media exposure around the time of their AGM, as shown by the positive and statistically significant coefficient on the Proximity to AGM_{fw} variable (second row). The coefficient on the interaction term confirms that ESG-related events receive more coverage as the distance between AGM and NGO campaigns shrinks. The result survives even after controlling for firm- and time-varying

effects captured by the lagged dependent variable (Column 2). Therefore, the analysis indicates that the AGM period intensifies media coverage. These results are consistent with Figure 2.C3 that shows that NGOs scrutiny increases during a firm's AGM period.[36]

Attention decay. How long does the AGM effect last? We modify (2.C1) by redefining the variable Proximity to AGM_{fw} and let it be 1 if week w is within $\pm k$ weeks from an AGM and 0 otherwise. We vary k between 1 and 24 weeks: Figure 2.C4 plots the estimated β_{treat} coefficients of the 24 regressions obtained by varying this variable in (2.C1) and the corresponding 95% confidence intervals. We find that news coverage increases with proximity to an AGM. The additional media coverage due to an AGM period is instead statistically indistinguishable from 0 when we consider AGM periods greater than 11 weeks, or over three months.

Conclusion. In summary, this analysis indicates that ESG-related events receive significantly more media coverage when they happen closer to an AGM. If the AGM is far in time, i.e., further than three months, these events do not benefit from the greater media attention that firms face during their AGM periods. Drawing a parallel with our analysis in the main text, the largest possible distance between the date of inclusion into the treatment (January 15, 2020) and the date of the latest possible AGM of a treated firm (April 15, 2020) is exactly three months. Thus, the distance between AGMs and donations must be smaller than three months for treated firms. To the extent that the empirical evidence on NGO campaigns translates to corporate donations, this analysis indicates that the AGM treatment successfully intensifies the media coverage of a firm's donations.

[36] As a robustness check, we investigate the rationale for the second peak in the density of NGO attacks detected 20 weeks after the AGM date in Figure 2.C3 of the main text. The data indicate that these NGO campaigns might be motivated by health-related awareness days that are typical of the month of October and November (e.g., Breast Cancer Awareness Month). If we were to exclude all NGO campaigns targeting healthcare firms, the peak around week 20 would drop substantially (not reported).

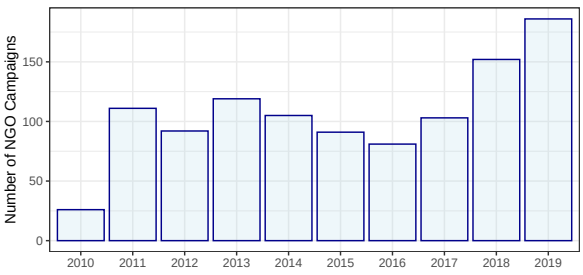


Figure 2.C1: NGO campaigns per year

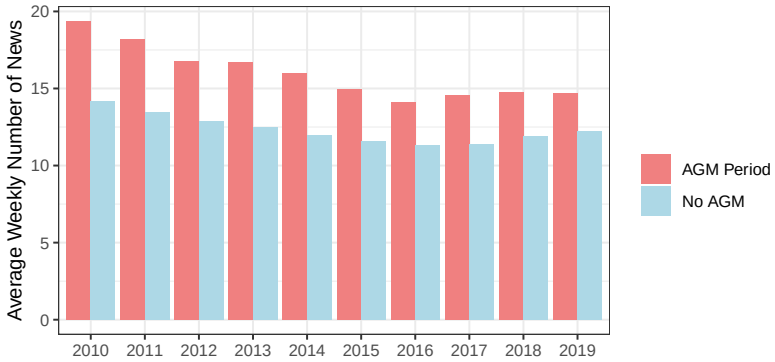
	Log Number of News	
	(1)	(2)
NGO	0.078*	0.066
	(0.046)	(0.048)
Proximity to AGM	0.260***	0.251***
	(0.009)	(0.009)
NGO × Proximity to AGM	0.383**	0.406**
	(0.168)	(0.170)
Lag Log Number of News		0.009***
		(0.0008)
Firm fixed effects	✓	✓
Week fixed effects	✓	✓
N	1,426,313	1,373,729
Adjusted R-squared	0.3938	0.3940

* − $p < 0.1$; ** − $p < 0.05$; *** − $p < 0.01$.

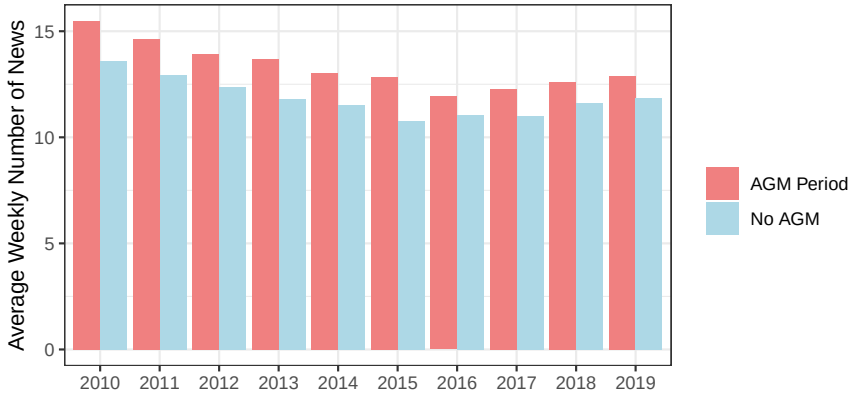
Table 2.C1: Media attention around AGMs

Note: The figure displays the yearly count of NGO campaigns targeting a company listed in the US from January 2010 to December 2019 (1,036 campaigns). The table presents the OLS regression coefficients from (2.C1). NGO is a dummy equal to one if firm f has been targeted by a negative NGO report during the current week. For firm f in week w Proximity to AGM is close to zero if firm f's yearly AGM is far away from week w and is 1 if, instead, its AGM is in week w. The regression includes firm- and week-fixed effects. The sample period goes from January 2010 to December 2019. Standard errors are clustered at the level of the firm and are reported in parentheses.

Figure 2.C2: Greater media coverage around AGM periods (red) than in other periods (blue)



(a) AGM Period defined as Within 10 Days



(b) AGM Period defined as Within 3 Months

Note: News coverage is much higher during AGM periods (red bars) than during other periods (blue bars). Extending the AGM period from a window of ± ten days (Panel a) to ± three months (Panel b), the distance between the two columns decreases, as the gap between news coverage during AGM periods and other periods is washed out by a greater interval. News data come from Ravenpack. AGM dates come from ISS.

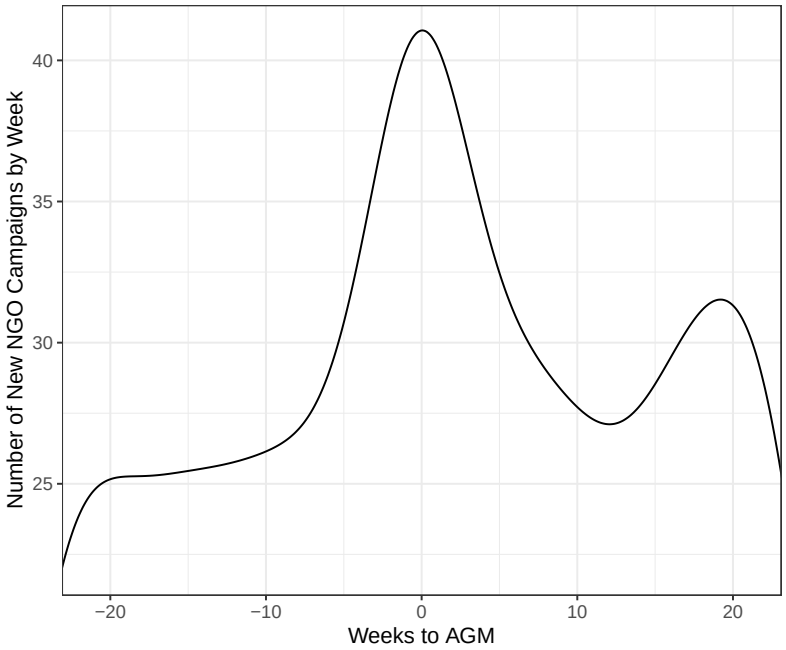


Figure 2.C3: Public scrutiny during AGMs

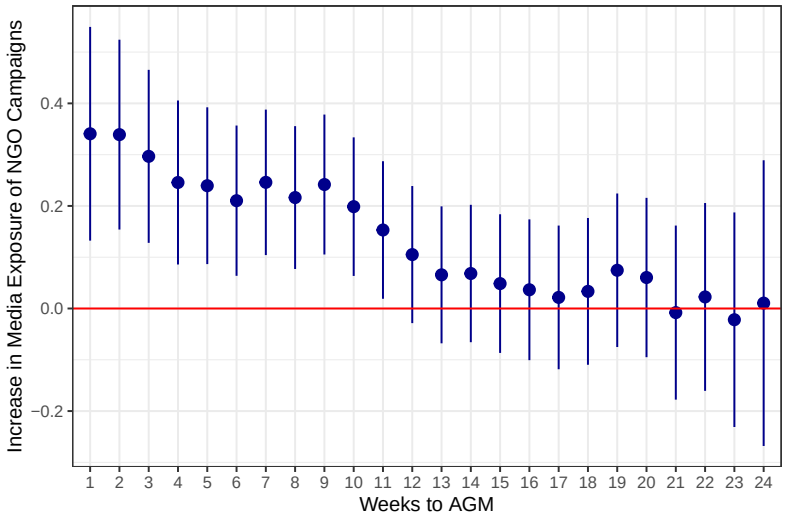


Figure 2.C4: Decay of media exposure

Note: Figure 2.C3 plots the density of NGO campaigns relative to the closest AGM dates of the targeted firms using pre-pandemic data from January 2010 to December 2019. The sample covers 4,676 US-listed firms and 1,036 high-severity NGO campaigns. The x-axis re-calendarizes time so that, for each year and firm, week 0 is the AGM week for all firms. Figure 2.C4 presents the beta coefficients from multiple regressions. Each coefficient comes from regressing the log of one plus the number of news about firm f in week w on a dummy indicating the publication of a negative NGO report about firm f in week w, a dummy equal to one when week w is less than k weeks away from the nearest AGM, where we take k to vary between 1 and 24 weeks, the interaction between these two dummy variables, and firm and week fixed effects. The figure reports the estimated interaction term as we vary k on the x-axis. The figure also reports the 95% confidence interval when the standard errors are clustered at the level of the firm. The sample period goes from January 2010 to December 2019 and covers 4,676 firms.

2.D Main Results with Alternative Datasets

The analyses in Section 2.4 use both financial and ownership data from Orbis, where, however, data for a few firms are missing. This section shows that the main results from that section are robust by drawing ownership data from another source, Refinitiv. The following exhibits present the analyses from Figure 2.1 and Tables 2.2 and 2.3 using the Refinitiv Consolited Ownership dataset. All the variables are defined as in Section 2.4.

Despite the different and slightly larger dataset, we find very similar results to those presented in the main text. Figure 2.D1 reports the coefficients from the event study in (2.3), which regresses whether a firm donated for covid before April 2020 on dummies indicating whether the firm held an AGM in the weeks between January 15 and June 15, 2020. As in Figure 2.1, only firms with individual shareholders (blue circles) are associated to a greater probability of donating. The difference between red triangles and blue dots is evident across the columns of Table 2.D1, which estimates coefficients that are almost identical to those in the main text. Finally, 2.D2 finds that the correlation between the donations of a financial shareholder and the firms in its portfolio is negative (and statistically significant) for blockholding shares ($\geq 2\%$).

Table 2.D1: Shareholders' influence on covid donations - different shareholding data

	Whether Firm f has Donated (0/1)					
	(1)	(2)	(3)	(4)	(5)	(6)
Ownership	-0.0092	0.0003	-0.0140	-0.0181	-0.0880***	0.0432*
	(0.0138)	(0.0128)	(0.0397)	(0.0276)	(0.0207)	(0.0209)
AGM	0.1104	0.1118	0.0809	0.1084	0.1143	0.1335
	(0.1244)	(0.1254)	(0.1345)	(0.1167)	(0.1287)	(0.1200)
Ownership × AGM	0.0808**	0.0828**	0.0574	-0.1664**	0.0013	-0.0846
	(0.0255)	(0.0265)	(0.0644)	(0.0667)	(0.0643)	(0.1361)
Ownership is defined as	Individuals			Institutional		
Ownership is the shares of investors owning:	$> 10\%$	$> 5\%$	$(0\%, 2\%)$	$> 10\%$	$> 5\%$	$(0\%, 2\%)$
Industry fixed effects	✓	✓	✓	✓	✓	✓
State fixed effects	✓	✓	✓	✓	✓	✓
Observations	482	482	482	482	482	482
Adjusted R-squared	0.2165	0.2166	0.2150	0.2208	0.2389	0.2184

* $-$ $p < 0.1$; ** $-$ $p < 0.05$; *** $-$ $p < 0.01$.

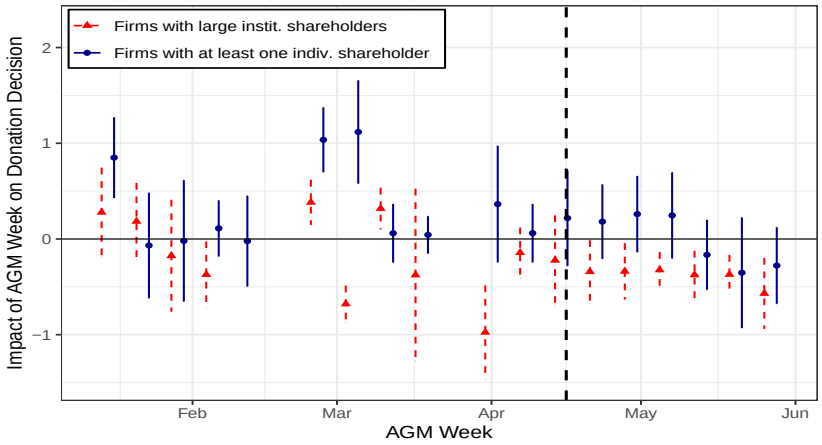
Note: The table presents the coefficients from OLS regressions of an indicator variable that is one if firm f has donated by April 15, 2020, on covariates. Compared to Table 2.2, this table uses ownership data from Refinitiv instead of Orbis. Italicized variables are defined in the middle panel. The variable *Ownership* is the share of either individual (Columns 1-3) or institutional investors (Columns 4-6) among all investors owning at least a share of total equity, as defined in the middle panel. Institutional investors include the largest financial investors in Table 2.1, namely, banks, mutual funds, and insurance firms. The variable *Ownership* is standardized. The AGM variable is an indicator variable taking value one if the firm has an AGM before April 15, 2020, and zero otherwise. All columns include industry- and state-fixed effects. Robust standard errors in parenthesis.

Table 2.D2: Correlation of donations of financial shareholders' and their portfolios

	Spearman Correlation
Minimum Equity Share Considered	Weighted Average × AGM [p-values]
(1)	(2)
0%	-0.082
(Avg. N = 374)	[0.668]
1%	0.073
(Avg. N = 75)	[0.840]
2%	-0.933
(Avg. N = 60)	[0.007]
3%	-0.889
(Avg. N = 66)	[0.044]
4%	-0.889
(Avg. N = 81)	[0.044]
5%	-0.943
(Avg. N = 52)	[0.057]

Note: This table shows a negative correlation between large institutional investors such as financial firms in the S&P 500 Index and the firms in their portfolio that had their AGMs before April 15, 2020. Compared to Table 2.3, this table uses ownership data from Refinitiv instead of Orbis. The negative correlation indicates that financial investors opposed COVID-19-related donations in their footprints. The table computes the Spearman correlation between whether a financial firm donates and the share of donations at the firms in its portfolio. In each row, we vary the minimum share % that a firm must have in another firm to be considered an investment according to the percentages reported in the first column. Column 1 also reports the average number of S&P500 firms in the portfolio of a financial investor in parenthesis. Column 2 considers only investments that got an AGM in the period under consideration (i.e., $\sum_j share_{ij} \times \mathbb{I}_{[\text{firm } j \text{ donated}]} \times \mathbb{I}_{[i\text{'s share in } j \text{ is greater than } x\%]} \times \mathbb{I}_{[j \text{ has an AGM}]}$). p-values testing whether the Spearman correlation is equal to zero are reported in square brackets.

Figure 2.D1: Influence on donations by AGM week and shareholder composition - different shareholding data



Note: The figure plots the estimated coefficients of an event study regressing whether a firm donated between January and April 2020 on dummies indicating whether the firm held an AGM in the weeks between January 15 and June 15, 2020. Compared to Figure 2.1, this table uses ownership data from Refinitiv instead of Orbis. The reference period is the week of June 15, 2020. Coefficients shown in circles are estimated using a sample of firms with at least one individual shareholder with at least 0.1% shares, and the triangles are from a sample of firms whose institutional blockholding (shareholders owning at least 5% a firm's equity as of December 2019) is greater than the median at S&P 500 firms. The vertical dashed line is on April 15, 2020, 90 days after the first US covid case.

2.E Private Sanctions on Russia

This section focuses on shareholder influence after Russia invaded Ukraine in February 2022 as an external validity exercise for the mechanism exposed in the main text.

Background and Data

On February 24, 2022, Russia started the so-called "special military operation." We take this date as the beginning of our sample. Sonnenfeld et al. (2022) list firms exposed to the Russian economy (e.g., exporters to Russia) that took a pro or against position vis-á-vis Russia.[37]

Data construction. We accessed this list on March 23, a month after the beginning of the invasion. The list contains 476 international firms operating in Russia at the time. Figure 2.E1a shows a breakdown of this sample based on different firm categories. Most of the observations belong to non-US firms (especially from the UK, Germany, and France) and international sports federations (e.g., UEFA), which quickly denied access to Russian sports teams in the days after the beginning of the invasion. We exclude these firms since our exogenous variation is based on the SEC rules and ISS requirements. Excluding another 12% of the observations that account for US non-listed firms for which we lack shareholding data, we are left with 164 US-listed firms for which the 2022 AGM date is available on the Refinitiv database.[38] This dataset is not the whole universe of US-listed firms operating in Russia but a collection of the firms that took actions, either pro or against Russia, in the first month of the war. By taking early actions, this dataset spans the firms that are most exposed to Russia, and thus, these firms are the most relevant for our analysis. 85% of the firms in this list have a market capitalization above $8bn, which is the limit for inclusion in the S&P 500 index.

Classification of firms' decisions. Sonnenfeld et al. (2022) categorizes firms as: (1) *Grade A - Surgical Removal, Resection* (51 firms) for firms that left Russia; (2) *Grade B – Keeping Options Open for Return* (69 firms) for firms that paused their ongoing projects; (3) *Grade C – Reducing Current Operations* (9 firms), for firms that paused certain operations; (4) *Grade D – Holding*

[37]The list is freely available at `https://som.yale.edu/story/2022/almost-500-companies-have-withdrawn-russia-some-remain`.

[38]We contacted Sonnenfeld about the data construction by email. On March 28, 2022, Professor Sonnenfeld informed us by email that "Our data sources are drawn upon multi-method anchoring with triangulation confirmation across expert and authoritative resources such as US Securities & Exchange Commission filings and along with other global regulatory reports; operational data available through Bloomberg; Thomson Reuters, and FactSet, company annual reports and shareholder communications, industry analyst reports, a wiki network of 300 company insiders across sectors and nations, personal exchanges with company executives, official company pronouncements on websites and press releases. We then review this data as a team in evaluating the categorizations."

Off New Investments/Development (27 firms), for firms that halted future investments; (5) *Grade F – Defying Demands for Exit or Reduction of Activities* (9 firms), for firms that kept working in Russia.

Data summary. Among the 164 firms in our database, 94 had an AGM in the three months following the outbreak of the war, whereas the 70 remaining firms had AGMs in another period. Table 2.E2 shows summary statistics comparable to those in Table 2.1 of the main text for the two groups. Column 3 performs balance checks over observable variables such as market capitalization, revenues, net income, fraction of revenues coming from the US and Canada, age of the CEO, ESG scores, average brokers' recommendations, and shareholding. Overall, control (treatment) firms are more represented in Grade A (D). The remaining two columns illustrate the variation in Grade across firms with at least 2% of individual shareholders or with at least 5% of institutional shareholders. Finally, Figure 2.E1b shows that, within sectors, firms are almost evenly distributed between treatment (blue) and control firms (red) – this further corroborates the exogeneity of selection into treatment.

Robustness Checks

Below, we present several robustness checks for the analysis in Section 2.4.5, which employed (2.2) to study whether firms with greater shares of large individual (institutional) blockholders support (oppose) exiting Russia. Arguably, outright exit is the highest possible sanction that firms can take against Russia, and it was not forced by international sanctions at the time. Of course, the optimal action might vary across sectors, as, for instance, internet firms might prefer to stay in Russia to disseminate Western information. For this reason, we exclude *Grade F* firms from the main analysis and include industry-fixed effects and several covariates.[39] Almost all firms have institutional blockholders with holdings greater than 2%; therefore, to properly capture individual shareholder's voice, we control for a dummy that is one if firm f has above the median blockholding of institutional investors and zero otherwise when Ownership_f refers to individual investors. This additional variable accounts for the fact that large institutional blockholders might reduce the effectiveness of individual shareholder voices, as shown in Section 2.2. Allowing for different intercepts based on shareholder composition ensures the identification of the coefficient of interest, β_{treat}.

[39]We include the fraction of revenues from America and Canada, the average broker recommendation, the age of the CEO, the net income, and industry dummies. Net income is highly correlated with the market capitalization (90%), EBIT (92%), and revenues (79%), which we, therefore, omit from the analysis. Including any of these variables in place of net income does not qualitatively affect the results.

Note. Because of space constraints, we report the full regression tables only for selected analyses. For the others, we only discuss the results, which are available upon request.

Measuring large blockholding. Tables 2.4 from the main text measures the association between a firm and its largest shareholders with a variable that is 1 if a firm has above the median value of blockholding of a specific shareholder reference group with at least a $x\%$ share and zero otherwise. We then vary x across columns to be greater than 10%, 5%, or 2%. If we used the underlying continuous variable instead, namely, the share of a certain group of shareholders (e.g., individuals) with at least a $x\%$ share, our results would not vary qualitatively.

Which institutional blockholders opposed exits? To better highlight the role of prominent shareholders in opposing exit decisions, we run the same analysis in (2.2) using *Above Median Blockholding*$_f$ as a measure of the association of a firm to its main shareholders. As in Section 2.4.5, this variable is 1 if the firm has above the median value of blockholding of a specific shareholder reference group with $x\%$ share and 0 otherwise. Table 2.E3 finds that mutual funds blockholders play the most important role, followed in order by banks and insurance companies, which is consistent with what we reported for the pandemic in Appendix Table 2.A3. This is probably because mutual funds are the largest shareholders in these firms (Table 2.E2), and they might be following their investments more actively than other investors due to their statutes.

Including *Grade F* firms. Excluding firms that announced that they would not exit Russia does not materially change our results. For instance, unreported analyses find that β_{treat} is 0.656 (S.E. 0.255) when the treatment group includes firms more exposed to individual shareholders with at least a 5% share and −0.320 (S.E. 0.157) for the similar analysis using institutional shareholders. These coefficients were 0.316 and −0.152 Table 2.4, which run the same analyses excluding the nine *Grade F* firms.

Excluding airline companies. Airline companies' decisions could be driven by Russia's ban on Western carriers from flying over the country. Excluding airline companies (3 observations: American Airlines, Delta Airlines, and United Airlines) does not change our results qualitatively.

Only S&P 500 firms in the list. Firms could be quite heterogeneous, and the decisions of small firms might not receive the same coverage as that of large firms. Excluding firms that are not on the S&P 500 list does not change our results qualitatively despite reducing the sample size to 103 observations only.

All S&P 500 firms. Selection might bias our analysis, as we do not observe the whole set of firms that deal with Russia but only a subset. To tackle this issue, we run (2.6) as described

above on all U.S.-listed S&P 500 firms. Since the firms that do not have business dealings with Russia will not make any decisions, we subset the dataset to consider only the firms whose exposure to Russia is greater than the median value observed among S&P 500 firms. Consistently, we find that the firms most exposed to large individual shareholders are most likely to exit Russia.

A different specification. The proposed regressions focus either on institutional or individual shareholders, while firm decisions might result from pressure from different shareholders. To account for this circumstance, we update (2.6) as follows:

$$\begin{aligned}\text{Exit}_f = \tilde{\beta}_0 + \tilde{\beta}_1 \text{AGM}_f \\ + \gamma_1 \text{Above Median Indiv. Block.}_f + \gamma_2 \text{ Above Median Indiv. Block.}_f \times \text{AGM}_f \\ + \theta_1 \text{Above Median Instit. Block.}_f + \theta_2 \text{ Above Median Instit. Block.}_f \times \text{AGM}_f \\ + \tilde{\beta}_2 \text{X}_f + \tilde{\varepsilon_f}, \end{aligned} \tag{2.E1}$$

where the coefficient vectors $\{\gamma_i\}_{i=1}^2$ and $\{\theta_i\}_{i=1}^2$ refer to either individual or institutional blockholders above the median level. Therefore, this specification simultaneously accounts for the effect of the treatment on both types of shareholders. The remaining variables stay unchanged. Table 2.E4 reports the results varying the thresholds of the blockholder definition and whether the reference institutional shareholders are all institutional shareholders (Columns 1 to 4) or only mutual funds (Columns 5 to 8). Overall, the results are in line with those presented in the previous analyses, not only in terms of the sign of the coefficients but also in terms of their magnitude: a shareholder's voice grows as the blockholding threshold increases.

Financials in 2022. Exit from Russia could be rather expensive, pushing firms with bad financial outcomes in 2022 to stay in Russia.For instance, Shell communicated that its exit from Russia would cost between $4bn and $5bn.[40] However, first, whether a firm had negative financial results is orthogonal to the timing of the AGM. Second, unreported results indicate that having a negative net income is not associated with Grade F and Grade A firms are not those with the largest profits. Similarly, Grade A firms are not the biggest and are rather comparable with Grade F firms in terms of market capitalization.

[40] CNBC reports that "Shell was forced to apologize on March 8 [2022] for buying a heavily discounted consignment of Russian oil. It subsequently announced that it was withdrawing from Russia." Source: `https://www.cnbc.com/2022/04/07/shell-to-write-down-up-to-5-billion-in-assets-after-exiting-russia.html`.

Dropping Russian Suppliers

This section extends Appendix 2.E by considering the decision to cut supply chain relationships with Russian corporations soon after the beginning of the invasion. To that end, we identify all relationships between US and Russian firms using Factset's Supply Chain Relationships data. We identify 102 US firms with an outstanding relationship with at least one Russian firm as of February 24, 2022, and with available shareholding and AGM data. Ninety-six also have all the control variables used in the preceding analysis available.

Table 2.E1: Blockholders' influence on the decision to cur supply chain relationships with Russian corporations

	Drop Relationship (0/1)	
	(1)	(2)
Above Median Blockholding	-0.107	-0.380***
	(0.129)	(0.060)
AGM	-0.159*	-0.103
	(0.088)	(0.072)
AGM × *Above Median Blockholding*	0.152	0.456***
	(0.186)	(0.112)
Threshold to be considered a blockholder:	>0%	>5%
Sector FE	✓	✓
Controls	✓	✓
N	96	96
Adjusted R-squared	0.1928	0.2079

* − $p < 0.1$; ** − $p < 0.05$; *** − $p < 0.01$.

Note: This table reports considers the influence of individual blockholders on US corporations' decision to cut relationships with Russian corporations in their supply chain after the beginning of the Ukraine invasion. It is the regression of a dummy equal to one if US firm f has stopped doing business with at least one Russian firm between February 24, 2022 and May 24,2022, on a dummy equal to one if the firm has a level of individual shareholding above median (Column 1) or a level of individual blockholding (5%) greater than the median (Column 2), a dummy indicating an early AGM (between February 24 and May 24, 2022), and the interaction between the two. The regressions also include sector fixed effects, and, as controls, the share of firm f's revenue coming from operations in the US and Canada, the share of revenue coming from operations in Russia, its CEO age, net income, and a dummy indicating an above-median level of institutional ownership.

Table 2.E2: Summary of the sample of listed firms exposed to the Russian economy by group

	(1)	(2)	(3)	(4)	(5)
	Annual General Meeting (AGM) between 02/22 and 05/22		p-values	Individual Shareholders	Institutional Shareholders
	Yes (treat)	No (control)	(1) - (2)	With ≥ 2%	With ≥ 5%
i. Firm Characteristics					
Market Cap (bn USD)	109.4	186.9	0.202	129.9	143.2
Brokers' Recommendation [-2, 2]	1.0	1.1	0.291	1.0	1.0
Revenue (bn USD)	33.2	35.1	0.849	33.8	33.5
EBIT (bn USD)	5.0	4.6	0.859	2.7	4.8
- EBIT > (dummy) 0	87.1	81.7	0.352	88.9	84.3
Net Income (bn USD)	4.9	5.6	0.724	2.5	5.3
- Net Income > 0 (dummy)	87.1	80.3	0.25	77.8	84.3
% of Revenues from US and Canada	51.8	51.9	0.98	51.9	52.0
CEO Age	61.6	60.4	0.337	62.1	61.0
ESG Score	71.3	66.6	0.101	63.5	69.2
ii. Shareholding (% Ownership)					
Share of Individual Investors With > 2%	1.4	3.3	0.15	13.6	2.0
Share of Institutional Investors With > 5%	28.6	25.0	0.08	23.7	27.9
- Mutual Funds	10.1	9.6	0.746	8.1	10.2
- Banks	0.5	0.0	0.07	0.2	0.3
- Insurance	1.1	0.0	0.029	0.0	0.6
iii. Corporate Actions as of March 23, 2022 (% of each group)					
Grade A - Surgical Removal, Resection (51 firms)	22.6	40.8	0.014	25.9	31.4
Grade B – Keeping Options Open for Return (69 firms)	41.9	42.3	0.968	55.6	42.1
Grade C – Reducing Current Operations (9 firms)	8.6	1.4	0.028	3.7	5.7
Grade D – Holding Off New Investments/Development (27 firms)	22.6	8.5	0.011	11.1	15.1
Grade F – Defying Demands for Exit or Reduction of Activities (9 firms)	4.3	7.0	0.462	3.7	5.7

Note: This table compares the firms in the treatment and control groups used in the empirical analysis of the corporate sanctions against the Russian economy executed in the first month of the 2022 war in Ukraine. This data was collected by Jeffrey Sonnenfeld and his team at Yale SOM, which we thank for sharing the data and explaining the data construction. Columns 1 focuses on firms with AGM within 3 months after the start of the war and Columns 2 the other firms. Column 4 focuses on firms with at least one individual shareholder owning more than 2% of total equity. Column 6 focuses on firms with at least one institutional investor owning more than 5% of total equity. Shareholding, profitability and control variables come from Refinitiv. The variable *Brokers' Recommendation* refers to the recommendations of equity analysts and it ranges between -2 and 2, where strong sell = −2, sell = −1, hold/neutral = 0, buy = 1, strong buy = 2. ESG score is the Social score of the firm as computed by Refinitiv.

Table 2.E3: Blockholders' influence on the decision to exit the Russian market after the invasion of Ukraine - breakdown by blockholder types

	Exited Russia (0/1)									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
AGM	−0.067	−0.094	0.144	0.043	−0.012	−0.022	−0.028	0.003	−0.032	0.098
	(0.090)	(0.090)	(0.115)	(0.111)	(0.085)	(0.086)	(0.090)	(0.091)	(0.089)	(0.099)
Above Median Blockholding	−0.547***	−0.428***	0.116	0.148	0.703***	0.423**	0.163	0.262	−0.067	0.206
	(0.181)	(0.128)	(0.132)	(0.137)	(0.193)	(0.213)	(0.264)	(0.272)	(0.181)	(0.129)
AGM × *Above Median Blockholding*	0.705***	0.263	−0.341**	−0.188	−0.584**	−0.309	−0.150	−0.332	−0.176	−0.293*
	(0.254)	(0.175)	(0.165)	(0.159)	(0.230)	(0.245)	(0.283)	(0.292)	(0.198)	(0.154)
Above Median Blockholding (0/1) defined for:	Individual		Institutional		Banks		Insurance		Mutual Funds	
Threshold to be considered a blockholder:	>10%	>2%	>10%	>2%	>2%	>1%	>2%	>1%	>10%	>5%
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Sector fixed effect	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
N	138	138	138	138	138	138	138	138	138	138
Adjusted R-squared	0.2762	0.2879	0.2642	0.2372	0.2818	0.2628	0.2280	0.2378	0.2397	0.2523

* − $p < 0.1$; ** − $p < 0.05$; *** − $p < 0.01$.

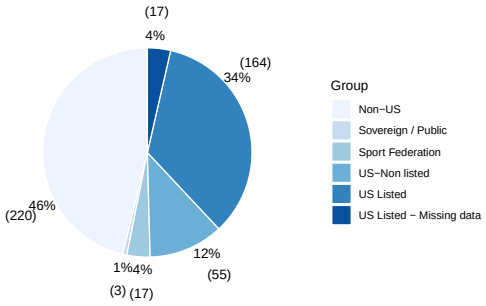
Note: This table indicates that banks and mutual funds mostly opposed exiting from Russia. The table reports the coefficients from OLS regressions of whether firm f has exited Russia as of March 23, 2022, on (i) the AGM treatment and (ii) a dummy *Above Median Blockholding* for whether the shareholders of firm f include blockholders with shares above the median value for that specific category, and (iii) their interaction. Categories vary across columns based on the reference shareholder type, and the minimum blockholding threshold considered and are defined in the middle panel. Firms with Grade F (i.e., firms that announced business as usual) are not included in the analysis. Institutional investors include mutual funds, banks, insurance, hedge funds, private equity, and venture capital. All columns include sector-fixed effects. Control variables include the share of revenues that come from activities in the US and Canada, brokers' recommendations, CEO age, and net income. Market capitalization, revenues, and net income are highly correlated; controlling for any of these two variables instead of net income does not change the results qualitatively. For models where individual investors are the reference category, we also include a dummy equal to 1 for above-median institutional ownership to account for the importance of institutional blockholders among the firms in this sample, and for the impossibility of exploiting firm fixed effects with only cross-sectional variations. Robust standard errors are reported in parenthesis.

Table 2.E4: Blockholders' influence on the decision to exit the Russian market after the invasion of Ukraine - simultaneous effect of different blockholder types

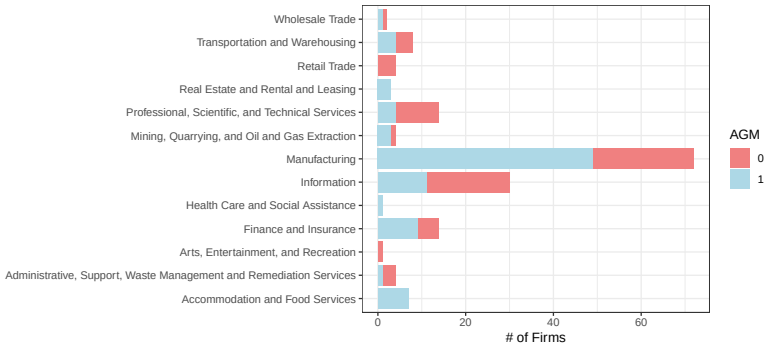
	Exited Russia (0/1)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
AGM	0.099	−0.014	−0.011	0.015	−0.067	0.055	−0.098	−0.093
	(0.114)	(0.112)	(0.112)	(0.105)	(0.089)	(0.096)	(0.110)	(0.111)
Above Median Indiv. Block.	−0.518***	−0.541***	−0.430***	−0.152	−0.531***	−0.548***	−0.419***	−0.191
	(0.189)	(0.144)	(0.125)	(0.141)	(0.184)	(0.131)	(0.130)	(0.146)
AGM × Above Median Indiv. Block.	0.786***	0.335	0.271	0.099	0.658**	0.344	0.245	0.114
	(0.238)	(0.254)	(0.173)	(0.183)	(0.269)	(0.230)	(0.183)	(0.191)
Above Median Institut. Block.	0.100	0.067	0.168	0.281*	−0.053	0.211*	0.028	0.037
	(0.125)	(0.123)	(0.129)	(0.144)	(0.171)	(0.119)	(0.117)	(0.136)
AGM × *Above Median Institut. Block.*	−0.326**	−0.136	−0.189	−0.282*	−0.175	−0.292**	0.023	0.023
	(0.163)	(0.150)	(0.150)	(0.165)	(0.189)	(0.145)	(0.146)	(0.164)
Above Median Institut. Block. (0/1) defined for:	All institutional investors				Only mutual funds			
Threshold to be considered a blockholder:	>10%	>5%	>2%	>1%	>10%	>5%	>2%	>1%
Sector FE	✓	✓	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓	✓	✓
N	138	138	138	138	138	138	138	138
Adjusted R-squared	0.3012	0.2915	0.2921	0.2666	0.2762	0.3140	0.2799	0.2341

* − $p < 0.1$; ** − $p < 0.05$; *** − $p < 0.01$.

Note: This table considers the influence of large institutional and large individual blockholders simultaneously. The regression equation is presented in Equation 2.E1; it regresses whether firm f has exited Russia as of March 23, 2022, on the (i) the AGM treatment and (ii) a dummy *Above Median Indiv. Blockholding* for whether the shareholders of firm f include blockholders with shares above the median value for individual shareholders, (iii) their interaction, (iv) another dummy *Above Median Institut. Blockholding* for whether the shareholders of firm f include blockholders with shares above the median value for that specific category, and its interaction with the AGM treatment. Categories vary across columns based on the reference institutional shareholder (either all institutions in Columns 1 to 4, or only mutual funds in Columns 5 to 8) and the minimum blockholding threshold considered, and are defined in the middle panel. Also, firms with Grade F (i.e., firms that announced business as usual) are included in the analysis. Institutional investors include mutual funds, banks, insurance, hedge funds, private equity, and venture capital. Control variables include the share of revenues that come from activities in the US and Canada, the exposure to Russia, brokers' recommendations, CEO age, and net income. Market capitalization, revenues, and net income are highly correlated; controlling for any of these two variables instead of net income does not change the results qualitatively. All columns include sector-fixed effects. Robust standard errors are reported in parenthesis.



(a) Surveyed firms



(b) Industry breakdown

Note: Panel (a) 34% of the firm surveyed in Sonnenfeld et al. (2022) are U.S.-listed firms. Panel (b) Number of firms by sector. Red (light blue) bars indicate control (treatment) group firms. Firms with a 2022 AGM scheduled between February 24 and May 24, 2022, are in the treated group as they have an AGM in the three months after February 24.

2.F Data on Donations and ESG between 2011-2021

This section describes the data used in Section 2.4.5. We gather donation news from Ravenpack by selecting all news in the “donation" category with a positive event sentiment for all U.S. firms, subsetting firms with an “entity relevance" score above 75%. The sample covers 2011 to 2021. We started from the whole universe of firms in Compustat covered by RepRisk during the whole sample period (2,722 firms). We kept firms listed on the NYSE or the NASDAQ and headquartered in the US, with no missing data in Compustat and in ISS, and whose Refinitiv ESG scores, historical shareholding data (the Refinitiv Ownership Database) were available. This narrows down the sample to 988 firms, accounting for 90% of the market capitalization of the original sample.

Table 2.F1 provides summary statistics on the market capitalization, number of ESG risk incidents, ownership data, and ESG scores for the companies in the sample. The average market capitalization is 53 billion dollars, ranging from 1 million to 1.7 trillion. Firms have, on average, 772 reported adverse ESG news (“ESG incidents”) during the period. Equivalently, a firm has a 30% chance of observing news in a given month. The summary statistics emphasize the holdings of individual and financial (“institutional") investors, which include Banks and Insurance Companies. ESG scores are expressed as a percentage, are scaled by industry and typically vary once a year.

Table 2.F1: Summary statistics of ESG data from 2011 to 2021

	Mean (1)	Median (2)	25% (3)	75% (4)	s.d. (5)
Market Capitalization (m USD)	21,269	4,831	1,553	16,192	60,631
RepRisk Incidents & Donations Data					
Number of Incidents	772.4	96	0	594	1,889.2
Number of E-Incidents	188.7	12	0	96	611.3
Number of S-Incidents	651.4	84	0	498	1,616.6
Number of G-Incidents	129.9	6	0	60	448.9
Probability of Having a High-Severity S-Incident (%)	4.5	0	0	0	27.3
Number of Donations	4.5	2	1	5	7.4
Ownership Data					
Individual Investor Ownership (%)	2.7	0	0	0.7	9.9
Institutional Ownership (%)	43.8	35.6	16.0	55.1	70.3
ESG Scores Data					
Environmental Score (%)	52.6	55.8	34.0	74.0	25.9
Social Score (%)	42.7	45.4	9.4	71.0	31.2
Governance Score (%)	54.4	58.1	37.8	75.1	25.7

Note: Summary statistics of the ESG Refinitiv news coverage data. Shares are computed over total equity. *Institutional Owernship* is the sum of the shares owned by Banks, Hedge Funds, Insurance Companues, Investment Advisors, Mutual Funds, Pension Funds, Private Equity, and Venture Capital firms. Risk Incidents data report the number of incidents observed by firms during the whole sample period.

Chapter 3

Promise at Dawn: Market Fragmentation and Liquidity when Dark Pools are Suspended*

Abstract

Should we regulate dark trading? This paper studies the effect of suspending dark pools on market fragmentation and liquidity. Using the European regulation MiFID II as a quasi-natural experiment, I show that dark volumes are redirected to lit venues and periodic auctions, in line with a "pecking order" of trading venues. Liquidity improves significantly on stock exchanges, and the effect is concentrated among stocks with a high level of noise trading. Those results confirm the theoretical prediction that dark trading is detrimental to liquidity by increasing adverse selection risk on stock exchanges.

*I wish to thank Hicham Abbas, Nicolas Coeurdacier, Thierry Foucault, Björn Hagströmer, Benjamin Marx, Albert Menkveld, Julien Pueblas, David Sraer, and participants to the Microstructure Course, Sciences Po Friday Seminar and CLS Seminar for fruitful conversations. I am thankful to Xavier Ragot and the OFCE for providing access to some of the data used in the paper. All errors are mine.

3.1 Introduction

Recent technological and regulatory changes have revolutionized the way stocks are traded. While national stock exchanges used to act as quasi-monopolists, trading in a share now takes place on multiple venues at the same time. The development of alternative, self-regulated trading venues has lead to lower fees and higher trading speed (Pagnotta and Philippon, 2018), but has also raised concerns about their impact on liquidity. Among them, dark pools have attracted a special attention from regulators and academics. By hiding their order book and offering potential price improvement, they are more likely to attract uninformed investors, increasing the share of informed traders on the reference lit exchange, which harms liquidity (Glosten and Milgrom, 1985, Zhu, 2014). However, estimating the impact of dark pools on stock exchanges' liquidity faces at least two challenges: *i)* there is no guarantee that orders sent to the dark would have been sent to lit venues - and not other trading venue types - in a world without dark pools, and *ii)* there is an endogenous relationship between liquidity and venue selection.

Using the European regulation MiFID II as a quasi-natural experiment, this paper studies the effect of banning dark pools on market fragmentation and liquidity. Implemented in 2018, MiFID II introduced a cap on the use of dark pools in the European Union. Over a rolling twelve-month period, trading of any stock across dark pools is limited to 8% of its volume. A breach of this threshold means that dark trading for that security is suspended for six months. More than 700 stocks were subject to that suspension on March 12, 2018, and the impact has been significant: European dark pools lost one-third of their market share, almost overnight. I develop a simple model based on Zhu (2014) that predicts that such regulation should significantly improve liquidity on stock exchanges. It also predicts that the effect should be stronger for more volatile stocks and stocks with higher levels of noise trading.

First, I estimate that between a third and a half of the dark volumes are redirected to reference lit exchanges when access to dark pools is suspended. The remaining dark volumes are mostly redirected to periodic auctions, while the impact on Systematic Internalisers, Over-the-Counter trading, and alternative lit venues is insignificant. Assuming that traders sort various trading venue types according to their cost and immediacy, a "pecking order" analysis (Menkveld et al., 2017) reveals that dark pools are in between lit venues and auctions. They attract relatively more patient traders than the former, and relatively more impatient traders than the latter. Banning dark venues introduces a direct trade-off between lit venues and auctions, explaining why those are the two venue types gaining market share after the ban.

Second, using the regulation to overcome the endogenous relationship between liquidity

and venue selection, this paper identifies the causal effect of the ban on liquidity. To ensure comparability between treated and control stocks, I first implement a propensity score matching procedure, based on pre-treatment baseline covariates, and run a two-way fixed effect regression on the matched sample. Then, I implement a Synthetic Difference-in-Differences approach (Arkhangelsky et al., 2021), with unit and time weights, based on pre-treatment liquidity measures. My results show that suspending stocks from trading in the dark narrows their spread by between 6 and 10% and the price impact by 5%.

Finally, I document that–in line with the theoretical predictions–the effect is concentrated among the most volatile stocks, and among stocks with a high level of retail ownership, a common proxy for noise trading (Foucault et al., 2011, Peress and Schmidt, 2019). A higher level of retail ownership is associated with a larger decrease in spread and price impact, but it is not associated with a stronger increase in the market share of the reference lit exchange. This last result confirms that it is the degree informativeness of orders, and not just trading volumes, that causes the liquidity improvement.

Taken together, those results are in line with the theoretical prediction that dark pools attract uninformed orders that would otherwise be sent to lit venues (Zhu, 2014). They tend to confirm that dark pools are detrimental to market quality by increasing adverse selection risk on stock exchanges. To summarise, banning dark pools redirects (some) trading volumes to reference lit exchanges, decreasing the share of informed trading and improving liquidity.

This paper's first contribution is to study dark pool suspensions rather than their introduction, in contrast to Hengelbrock and Theissen (2009) and Boneva et al. (2016). I exploit a clean, exogenous shock that does not require a two-stage estimation procedure with the use of an instrument. Comerton-Forde and Putniņš (2015) instrument the level of dark trading for a stock with the average level of dark trading in a basket of shares of the same size group, minus the stock of interest and find a positive relationship between the level of dark trading and the bid-ask spread. My findings are complementary to theirs as they document that an increase in dark trading from zero to 10% of total trading volume increases the spread by 11%.

Other studies have used a regulatory change as an exogenous shock to dark trading. Kwan et al. (2015) exploit a difference in regulatory treatment between trading venues in the United States to assess the impact of dark pools on other exchanges' competitiveness. Foley and Putniņš (2016) and Comerton-Forde et al. (2018) study the introduction of a new regulation forcing dark pools to guarantee a minimum price improvement of one tick size relative to the National Best Bid-Offer in Canada and Australia in 2012 and 2013 respectively, and which led the average level of dark trading to fall by almost 30%. Foley and Putniņš (2016) find a strong

and significant negative relationship between dark trading and exchange spreads, meaning that dark pools benefit market liquidity. In contrast to this paper, an increase in dark trading of 5% of total dollar volume decreases spreads by around 2%.

Finally, Johann et al. (2019), and Neumeier et al. (2023) study the same regulation as this paper. Johann et al. (2019) use different econometric settings, finding different results, and do not investigate the channel through which dark trading alters liquidity. Neumeier et al. (2023) focus on investors' trading costs, and find that dark pools indeed offer lower execution costs.

The remainder of the paper is organized as follows. Section 2 derives simple theoretical predictions regarding the suspension of dark pools on liquidity. Section 3 reviews the recent regulatory developments in the European trading landscape. Section 4 presents the data and the empirical strategy. In Section 5, I develop a "pecking order" analysis explaining why dark volumes are redirected to lit venues and auctions after the suspensions. Section 6 causally identifies the impact of dark trading on liquidity by using the regulation as a quasi-natural experiment. Section 7 concludes.

3.2 Theoretical Predictions

This section develops a simplified version of Zhu (2014), and describes a mechanism through which the suspension from trading in a dark pool is expected to be beneficial to a lit exchange's liquidity. While I impose somewhat stricter assumptions, I can predict the impact of dark trading on the bid-ask spread and the price impact in a tractable setting.

3.2.1 Assumptions

There is one trading period. At the end of the period, an asset pays an uncertain dividend equally likely to be σ or $-\sigma$, and is publicly revealed after trading.
Two trading venues operate simultaneously: a lit exchange and a dark pool. On the exchange, a risk-neutral market-maker (*she*/*her*) sets the bid-ask spread such that she breaks even on average.[1] Sell orders are executed at the bid and buy orders are executed at the ask. The spread is symmetric around the initial expected value of the dividend from the point of view of the market maker, which is zero. Then the ask price is defined as S and the bid price as $-S$. The dark pool matches buyers and sellers at the mid-point of the lit exchange's bid-ask.

[1]Making the market-maker risk averse would incorporate an inventory risk effect, adjustable in the long-run. It is not necessary here, as the ban from dark pools is only temporary.

Such a dark pool falls into the scope of dark trading activities regulated under MiFID II's Double-Volume-Cap mechanism studied in this paper. An order submitted to the dark pool contains no price information and is invisible to anyone but the sender. Orders on the heavier side of the market are randomly matched with orders on the lighter side of the market.
There are two types of traders: informed traders and noise traders. Informed traders benefit from preferential information about the value of the dividend and know for sure whether it is going to be σ or $-\sigma$. In case of the realization of σ, all informed traders are buyers (and sellers in case of $-\sigma$). Informed traders constitute a fraction α of the total mass of traders. noise traders (fraction $1-\alpha$) assign equal probability to the two possible outcomes of the dividend. Noise buyers and noise sellers represent each half of the mass of noise traders.
Noise traders act as brokers and trade on behalf of an external investor: they do not benefit from the outcome of the dividend and are incurred a cost c_i if they have not bought or sold the asset by the end of the period.[2] c_i is randomly distributed following a Cumulative Distribution Function $G : [0, \Gamma] \to [0, 1]$, with $\Gamma \in]0, \infty)$.
Traders arrive separately, can trade only one unit of the asset, and must choose to which venue they send their order. Both exchanges do not require any trading fee.

3.2.2 Dark Trading and the Bid-Ask Spread

β is the share of informed traders who choose to trade in the dark, and γ as the share of noise traders who choose to trade in the dark.

Equilibrium Spread Without a Dark Pool. I first derive the spread when both β and γ are equal to 0, that is, the no-dark pool equilibrium. The lit exchange's market-maker must break even on average and thus will choose the spread, S^{NoDark}, such that

$$0 = -\alpha(\sigma - S^{NoDark}) + (1-\alpha)S^{NoDark}$$

The equilibrium value of S^{NoDark} is

$$S^{NoDark} = \alpha\sigma. \tag{3.1}$$

The spread is proportional to the share of informed traders on the exchange.

Equilibrium With a Dark Pool. In the case where a dark pool is operating, alongside the lit

[2]Here, noise traders can be thought of as brokers trading for an asset manager rebalancing their portfolios. They do not own the asset after buying it, and the delay cost can either be seen as reputational damage or as the forgone trading fee they charge to their client.

exchange, the risk-neutral market marker sets the spread, S, such that

$$0 = -\alpha(1-\beta)(\sigma - S) + (1-\alpha)(1-\gamma)S,$$

rearranging,

$$S = \frac{\alpha(1-\beta)}{\alpha(1-\beta) + (1-\alpha)(1-\gamma)}\sigma < \sigma. \tag{3.2}$$

Which is similar to Zhu (2014).
From now on and for simplicity, let's assume that the realization of the dividend is σ (one can show that all equations are symmetric in the case $-\sigma$ is realized). Informed traders face a crossing probability in the dark

$$r^- = \frac{\frac{1}{2}(1-\alpha)\gamma}{\frac{1}{2}(1-\alpha)\gamma + \alpha\beta}. \tag{3.3}$$

r^- is the ratio of sellers over buyers in the dark pool.

Noise traders, on the other hand, don't know on which side of the market they are. In case they are on a different side of the market than informed traders, their probability of crossing is 1 ($r^+ = 1$). As they assign an equal probability to both events, their expected probability of being matched in the dark is

$$\bar{r} = \frac{1 + r^-}{2}. \tag{3.4}$$

Turning to the equilibrium trading strategies, informed traders have the following expected payoffs:

$$\begin{cases} E^I[\mu]_{Exchange} = \sigma - S \\ E^I[\mu]_{Dark} = r^-\sigma \end{cases}$$

noise traders have the following expected payoffs:

$$\begin{cases} E^L[\mu]_{Exchange} = -S \\ E^L[\mu]_{Dark} = -(1-\bar{r})c_i \end{cases}$$

Contrarily to Zhu (2014), it is never in a trader's interest to delay a trade. γ is the proportion of noise traders with a fee c_i too low (or a crossing probability too high) to be incentivized to trade on the exchange,

$$\gamma = G\left(\frac{S}{1-\bar{r}}\right).$$

An equilibrium is defined when the marginal informed trader is indifferent between the two

venues, with β and γ strictly between 0 and 1, and $0 < r^- < \bar{r} < 1$, for $0 < \alpha < 1$.

The equilibrium condition ensures that

$$\sigma - S = r^- \sigma.$$

The equation can be rewritten as

$$1 - \frac{S}{\sigma} = r^-. \tag{3.5}$$

Replacing S and r^- by their values from Equations (2) and (3), and solving for β as a function of γ gives

$$\beta = \frac{\gamma}{2 - \gamma}. \tag{3.6}$$

(3.6) says that in equilibrium, β is always smaller than γ. That means that the relative share of informed traders on the exchange increases when a dark pool is introduced. Replacing the equilibrium value of r^- in the expression for γ yields:

$$\gamma = G(2\sigma), \tag{3.7}$$

which means that the level of dark trading is solely determined by the volatility of the asset.

The expression for the spread simplifies to:

$$S = \frac{2\alpha}{2 - (1 - \alpha)G(2\sigma)}\sigma, \tag{3.8}$$

which is unique.

Prediction 1: *Suspending the access to the dark pool narrows the bid-ask spread.*

Suspending the access to the dark pool reduces the exchange's spread by

$$\frac{S^{NoDark} - S}{S} = -\frac{(1 - \alpha)G(2\sigma)}{2} < 0. \tag{3.9}$$

The dark pool attracts more noise traders, because their expected crossing probability in the dark is higher than that of informed traders. On the other hand, informed traders want to benefit from their preferential information about the future value of the dividend and wish to make sure to trade before the end of the period. Moreover, they know that they are on the heavier side of the market and that their expected crossing probability is low in the dark. Thus, the market-maker is forced to deal with relatively more informed traders than in the case with

no dark pool, and is forced to increase her spread to break even. Suspending the access to the dark pool redirects relatively more uninformed orders, reducing adverse selection on the exchange. The spread thus narrows.

> ***Prediction 1.1****: The reduction in spread is larger for more volatile stocks.*

As the asset's volatility increases, the share of uninformed traders choosing to trade in the dark increases. The share of informed traders trading in the dark also increases, but at a slower rate, leading to more adverse selection on the lit exchange.

> ***Prediction 1.2****: The reduction in spread is larger for stocks with a higher share of noise trading.*

Similarly, when the share of noise traders increases, the market share of the dark pool is greater. The share of noise traders on the exchange increases - leading to a lower spread - but at a slower rate. There is a bigger change in the relative share of noise traders on the exchange when the access to the dark pool is suspended.

3.2.3 Dark Trading and the Price Impact

At the end of the trading session, the market-maker observes the volumes of buy and sell orders, V_b and V_s. The closing price is set equal to her expectation conditional on V_b and V_s:

$$P_1 = (2 * P(\sigma|V_b, V_s) - 1)\sigma. \tag{3.10}$$

T, the total trading volume, is defined as $T = V_b + V_s$. Then, V_b can be seen as the realizations of a binomially distributed random variable, X, after T draws. Then,

$$P_1 = \left(2 * \frac{P(X = V_b|\sigma)}{P(X = V_b|\sigma) + P(X = V_b| - \sigma)} - 1\right)\sigma, \tag{3.11}$$

using Bayes' rule and the fact that the original belief of the market-maker is $P_0(\sigma) = 0.5$. Using the properties of the binomial distribution, this can be expressed as

$$P_1 = \left(\frac{1 - \left(\frac{1-P(B)}{1+P(B)}\right)^{V_b - V_s}}{1 + \left(\frac{1-P(B)}{1+P(B)}\right)^{V_b - V_s}}\right)\sigma, \tag{3.12}$$

where $P(B)$ is the probability of receiving a buy order. I define the price impact as the sensitivity of the closing price to a change in the order imbalance:

$$\frac{\partial P_1}{\partial (V_b - V_s)} = \sigma \left(- \frac{2 \left(\frac{1-P(B)}{1+P(B)} \right)^{V_b - V_s} \ln \left(\frac{1-P(B)}{1+P(B)} \right)}{\left(\left(\frac{1-P(B)}{1+P(B)} \right)^{V_b - V_s} + 1 \right)^2} \right) > 0, \tag{3.13}$$

where the inequality holds as $\ln \left(\frac{1-P(B)}{1+P(B)} \right) < 0$.

Prediction 2: *Suspending access to the dark pool reduces the price impact.*

When there is a dark pool operating alongside the lit exchange, there are relatively more informed traders left on the exchange. Thus, the probability of receiving a buy order, $P(B)$ is greater. Deriving (3.13) with respect to $P(B)$ yields:

$$\frac{\partial (3.13)}{\partial P(B)} > 0. \tag{3.14}$$

Intuitively, when a dark pool is operating, the probability that an additional buy order comes from an informed trader is greater, making the market-maker update her beliefs more quickly. Suspending the access to the dark pool redirects relatively more noise traders to the lit exchange, decreasing the signal-to-noise ratio.

In addition, $(V_b - V_s)$ is always greater when there is no dark pool.[3] The suspension of the dark pool has then also a volume effect: the market-maker faces a greater crowd of traders, making every additional order less informative ($\frac{\partial (3.13)}{\partial (V_b - V_s)} < 0$).

Prediction 2.1*: The reduction in price impact is larger for more volatile stocks.*

In the dark pool case, greater volatility strictly increases the price impact by two channels. Increasing the market share of the dark pool first makes the order flow on the exchange more informative. Every order, more likely to come from an informed trader, makes the market-maker update her belief more quickly. Secondly, it decreases the number of traders left on the exchange: the first orders are always the most informative. A greater volatility unambiguously increases the price impact relative to the no dark pool, benchmark, case.

The role of α is itself ambiguous. An increase in the share of informed traders increases linearly the probability of receiving a buy order in the no dark pool case ($P(B) = 0.5 + 0.5\alpha$), but its

[3] $(V_b - V_s)$ simplifies to $\frac{ST}{\sigma}$.

impact on $P(B)$ in the case with a dark pool is concave. It is not possible to derive a general rule regarding whether stocks with a higher share of noise trading would be more impacted by a dark pool ban. In general, for $\alpha < 0.1$, a greater α means a greater improvement after the dark pool suspension, but it is the reverse for higher values of α.

Those predictions rely on a key mechanism: orders sent to the lit exchange are more informed, and suspending access to the dark pool redirects relatively less informed orders to the main exchange. There exists empirical evidence that orders sent to dark pools are less informed than orders sent to lit venues. By studying the impact of dark trading on price discovery, Comerton-Forde and Putniņš (2015) document that as more orders for a stock are sent to dark venues, their contribution to price discovery increases at a slower rate than their volume share, indicating that dark trades on average contain less private information than lit trades. Menkveld et al. (2017) study the changes in market share between different types of trading venues right after macroeconomic news and unexpected company announcements and show that these factors, which can be regarded as shocks to information, make the share of lit trading jump, at the expense of dark venues. The adverse-selection mechanism echoes Peress and Schmidt (2019), who show that when noise traders are distracted and trade less, liquidity worsens. As in this paper, the underlying mechanism is a sudden change, short-term in the level of noise trading in a stock exchange. This contrasts with Foucault et al. (2011), who study a permanent, long-term change in the level of noise trading, and where inventory concerns from market makers predominate, leading to a negative relationship between the level of noise trading and liquidity.

3.3 Institutional Background

3.3.1 The Fragmentation of Public Equity Markets

The *Markets in Financial Instruments Directive* (MiFID) came into force in 2007 and introduced a market structure framework that facilitated the emergence of dark pools. Its primary goal was to liberalize the market for equity trading in Europe. MiFID increased the competitiveness of financial markets by abolishing the *Concentration Rule* that allowed member states to require investment firms to route orders only to stock exchanges.[4] It recognized new categories of trading venues, with different regulatory statuses. More specifically, it established rules under which Multilateral Trading Facilities, self-regulated trading venues, could be registered and

[4]As part of the *Investment Services Directive*, the European financial markets' legal framework since 1993 and revoked by MiFID.

operated. With the removal of barriers to competition, the market for equity trading became significantly more fragmented: the share of equity trading on MTFs in Europe increased from 0% in 2008 to almost 20% by 2011 (Fioravanti and Gentile (2011)).

Further regulatory changes strengthened the demand for dark venues. MiFID made it mandatory for trading venues to display bid and offer prices and depth of the order book (volumes available for trading at different prices) on a continuous basis. Such pre-trade transparency disclosure increased the probability for senders of large orders to be detected by predatory traders. In order to protect investors from 'front-running', MiFID provided exemptions from pre-trade transparency.[5] It includes venue-wide exemptions for venues that do not match trades based on their own order books, but instead match orders at a price "determined in accordance with a reference price generated by another system, where that reference price is widely published".[6] Most dark pools in Europe rely on this exemption in order to allow their clients to trade without pre-trade transparency, and match volumes using the displayed best bid-ask prices from one or more regulated markets. Dark pools offer price improvements over market orders on lit venues because the execution price is usually the mid-point of the current bid-ask spread on an external venue (Petrescu and Wedow (2017)). Consequently, there is no market impact cost, as the price is unrelated to the volumes traded. However, dark pools do not have as much liquidity as lit venues and thus once an order is sent, the time for a matching order to arrive is longer, leading to slower execution speeds. They automatically match buyers and sellers at a specified price, and investors cannot infer their expected speed of execution from the order book. Any order imbalance will force traders on the heavier side of the market to wait before their order is matched. This slower speed of execution can incur significant costs, especially if the order is not filled during the day (Petrescu and Wedow (2017)). In compensation, they offer a price improvement, increasing in an asset's illiquidity. [7]

The aggregate impact of dark pools on market functioning has been the subject of debate among regulatory authorities and academics. Fragmentation between dark and lit venues results in changes in market structure and dynamics. The International Organization of Securities Commissions identified liquidity as a channel through which dark trading could be detrimental to market quality. The trade-off between speed of execution and price improvement

[5]Those exemptions occur in four cases: *Large in Scale* transactions (large orders), transactions based on a reference price generated by another system, negotiated transactions and orders held in an order management facility of the trading venue.

[6]Commission Regulation No 1287/2006, Article 18.

[7]Ready (2014) documents that dark pools attract a lower share of trades in stock with lower spreads, as the gains from trading at the midpoint might not be as high.

makes dark pools more attractive to uninformed traders, and the clustering of informed orders on lit market, more likely to be on the same side, could alter liquidity. Those fears have fueled the work of European legislators over MiFID II.

3.3.2 From MiFID to MiFID II

MiFID II, together with its accompanying regulation MiFIR, was adopted by the European Council in May 2014 and replaced MiFID in January 2018 under the supervision of the *European Securities and Markets Authority* (ESMA), the EU's markets regulator.[8] MiFID II maintains the pre-trade exemptions but introduces certain restrictions. The "Double-Volume-Cap" (DVC) mechanism limits the use of the reference-price exemption.[9] If MiFID II, as a whole, was implemented on January 3 2018, the implementation of the DVC mechanism was delayed because the regulator lacked the proper data.[10] From March 2018, every month, the dark volume over the last 12 months of every share traded in the EU is calculated, if more than 8% of the total volume for a stock has been in all dark pools combined, it cannot be traded in a dark pool under the reference-price exemption for 6 months, with a one-month delay.[11] The suspension on March 12, 2018, was based on estimates from January 2018 (calculated between January and December 2017) and February 2018 (calculated between February 2017 and January 2018).

From the 26,037 securities under the ESMA's jurisdiction as of March 7, 2018, only 3,949 had been traded at least once in a dark pool over the last twelve months. 736 securities were suspended from all dark venues on March 12, and they represented more than 50% of dark volume between March 2017 and March 2018. The impact of MiFID II on dark pools has been substantial. Figure 3.1 shows the market share of dark pools in Europe from January 12 to May 12, 2018. The average daily market share of dark pools in European markets fell from 8.45% before the first wave of suspensions to 5.7% after the suspension. Dark pools have lost about one-third of their market share, almost overnight.

[8] The *Directive on markets in financial instruments repealing Directive 2004/39/EC of the European Parliament and of the Council* and the *Markets in Financial Instruments Regulation* constitute the new legal framework introduced in January 2018, commonly referred to as "MiFID II".

[9] Article 5, *Markets in Financial Instruments Regulation* (MiFIR).

[10] "ESMA delays publication of Double-Volume-Cap data", ESMA Press Release, January 9, 2018.

[11] Article 5, MiFIR. It also suspensions shares from a single dark pool if it represents more than 4% of the total volume traded over the last 12 months.

3.4 Empirical Approach

This section describes the sample selection procedure, the data sources and an overview of the effect of the ban on market fragmentation and common liquidity measures.

3.4.1 Data

Sample Selection. 25,336 securities are reported in all three ESMA DVC files from January, February and March 2018, covering the entire universe of equity trading in Europe. The ESMA's DVC files provide information about the total trading volume over the twelve months before publication, as well as the share of dark trading under the reference-price exemption over the same period for each security. 1,479 securities are liquid shares (according to ESMA's classification) and have a 2017 trading volume greater than 5 million euros. Those filters ensure that all the stocks in the sample are actively traded. 1,458 have either been suspended from all dark pools for 6 months on March 12, 2018, or not suspended at all until May 11, 2018. 918 of them have all their data available in Refinitiv, have their Relevant Competent Authority from a set of core EU countries (Table 3.A1, in Appendix), and their company headquarters and listing stock exchange based in the EU. 898 ISIN are identified as being the primary issuance for the company, and 865 are quoted in a European currency.[12] Finally, I delete stocks with more than one-third of observations with zero volume and those subject to regulatory mistakes.[13] The final sample comprises 865 securities, listed in 12 countries and spanning across 11 sectors (Tables 3.A2 and 3.A3, in Appendix). The sample is divided between 450 securities suspended from dark pools on March 12, 2018 (referred to as the *treated units*), and 415 not suspended from dark trading until at least May 2018 (referred to as the *control units*). Figure 3.2 plots the distribution of the share of dark trading of stocks in the sample as of March 2018, when the first wave of suspensions occurred. The observations prior March 9, 2018 (included) will be referred to as the *pre-treatment period*, and observations from March 12, 2018 will be referred to as the *post-treatment period*.

Sources. For each stock in the sample, I collected by hand their Market Share Reporter (MSR) for the period from January 29 to April 26, 2018, on Refinitiv. The MSR displays the daily trading volume on all venues for a given ISIN. The MSR reports all Reuters Instrument Codes (RIC) for a given ISIN (an ISIN typically has one RIC per trading venue where the stock is

[12]The set of European currencies chosen is: EUR, CHF, DKK, GBP, PLN and SEK

[13]Is considered a regulatory mistake a stock with a share of dark trading greater than 8% and not suspended, or a stock with a share of dark trading lower than 8% and suspended.

traded). I collect most of the data from Refinitiv.
Noise trading is often proxied by the level of retail ownership. However, in many countries, investors are not required to disclose their holdings under a certain threshold (De La Cruz et al. (2019)). I retrieve, from Orbis, the level of retail ownership for approximately 17% of stocks in the sample. I complement these data with the level of non-institutional ownership from Refinitiv, highly correlated with the former measure.[14]

Variables. All prices are expressed in Euros, based on the closing exchange rate as of January 3, 2018. The main liquidity measures are the quoted bid-ask spread and the Amihud ratio, computed as in Peress and Schmidt (2019). Each stock's intraday volatility is computed using the price range, as suggested in Rogers and Satchell (1991).[15] It is an estimator for measuring the volatility of securities with an average return not equal to zero. It has been shown that this estimator is robust to microstructure noise (Alizadeh et al. (2002)). I use three measures of the spread: the quoted spread on the reference lit exchange, the simple average spread on all other lit venues, and a volume-weighted average spread on the non-reference lit venues.

3.4.2 Descriptive Statistics

Summary statistics are provided in Table 3.1. It provides information about the distribution of the pre-treatment average of the main variables. The average market capitalization is around 10 billion euros, driven by some very large caps, as the median is only 2.8 billion. The table reports both the average trading volume on the reference lit exchange and the total trading volume across all venue types. The reference lit exchange represents typically between 15 and 50% of the overall trading volume, and has the highest level of liquidity: the average bid-ask spread is 10 to 20 times narrower than the simple average bid-ask spread on all other lit venues, and 2 to 5 times lower than the volume-weighted average bid-ask spread on other lit venues. A breakdown of market share by trading venue type, group and period is given in Table 3.2. Lit trading represents roughly half of all trading for stocks in the sample, and Systematic

[14]For stocks with both measures available, the correlation coefficient is 0.5, statistically significant from 0 at the 1% level.

[15]The formula is as follows:

$$V_{i,t} = \sqrt{\log\left(\frac{High_{i,t}}{Close_{i,t}}\right) * \log\left(\frac{High_{i,t}}{Open_{i,t}}\right) + \log\left(\frac{Low_{i,t}}{Close_{i,t}}\right) * \log\left(\frac{Low_{i,t}}{Open_{i,t}}\right)} \tag{3.15}$$

where, for a stock i on day t, $open_{i,t}$ and $Low_{i,t}$ are the opening and closing prices, $High_{i,t}$ and $Low_{i,t}$ are respectively the highest price at which a trade for stock i occurred during the trading day t, and the lowest price at which a trade occurred for the same security.

Internalisers have a market share of between 25 and 30%. The level of dark trading during the pre-treatment period (January 29 - March 9, 2018) is significantly lower than its 2017 value. This is due, in part, to a large decrease in dark trading following the announcement of the DVC mechanism and the implementation of MiFID II.

Comparing the evolution of the market share of different venue types between treated and control stocks, the ban seems to have maintained the market share of lit venues to its pre-ban level, while it has decreased for control stocks. This could be due to the fact that the month of January 2018 suffered from a large market sell-off. Such market conditions generally benefit lit exchanges. Auctions seem to have benefited from the ban, as their market share grew from 9 to almost 11% for treated stocks, while they gained only 0.3% of market share among control stocks. For both groups, the share of SI increased significantly, but even more so for control stocks. Those facts are shown in Figure 3.4: the reference lit exchange and auctions see an increase in market share among treated stocks following the ban, while the share of dark pools falls. We also see a short-lived, positive effect of the ban on other lit venues.

Turning to liquidity measures, Table 3.3 reports the average bid-ask spread and Amihud ratio by group and period. Treated stocks seem to be more liquid: their spread is 20 to 30% narrower, and the Amihud ratio is 40 to 50% smaller. Looking at the difference in average liquidity measures over time (Figure 3.3), there seems to be a liquidity improvement for treated stocks following their ban from dark pools.

3.4.3 Empirical Strategy

Where have the dark volumes gone? A key step in the process of evaluating the impact of dark pools on liquidity is to determine where dark orders would have been sent if dark pools were suspended. This paper develops a "pecking order" (Menkveld et al. (2017)): when executing orders, investors sort the different venue types according to a trade-off between liquidity costs and immediacy. In this order, low-immediacy-low-cost venues are at the "top" of the order, and both the immediacy and the cost increase as we go down the order. It predicts that, as trading needs become urgent, investors favor costly, high-immediacy venue types (lit venues for instance) at the expense of cheap, low-immediacy venues, going down the pecking order. The main assumption in this paper is that once dark pools are suspended (removed from the pecking order), investors choose to send their order to the closest alternative, meaning the venue type either right above or below dark pools in the pecking order. While the objective of the DVC was to bring back volumes to the reference lit exchanges, many practitioners

predicted that they would be redirected to SI instead. [16] As seen on Figure 3.4, it does not seem to be the case, and the pecking order could explain.

Following Menkveld et al. (2017), I test the pecking order hypothesis using urgency shocks, proxied by innovations to the VSTOXX level (the European equivalent to VIX): days with unexpectedly high VSTOXX level should urge investors to trade more quickly, and thus to go "down" in the pecking order. Venue types that see the largest increase in market share on those days should be venues at the bottom of the pecking order. Comparing the change in market share for dark pools with that of other venues allows us to determine which venues are the closest substitutes.

Impact on Liquidity As volumes seem to be redirected, in part, to the reference lit exchange, we are interested in the liquidity impact of the ban. The treatment being assigned solely on the basis of a cut-off score on a pre-treatment variable, an intuitive approach to estimating the impact of the suspension on liquidity would be to implement a Regression Discontinuity (RD) Design. However, a key assumption underlying that approach is the continuity of observed baseline covariates around the cutoff (Lee and Lemieux (2010), Calonico et al. (2014)). If the treatment and control groups are different on average, we have to investigate whether the difference in covariates is smooth around the 8% threshold. However, if there are several covariates to be tested, some might exhibit a discontinuity by random chance. In such a case, Lee and Lemieux (2010) suggest using Seemingly Unrelated Regressions (SUR). It takes the form of a system of equations, one for each covariate k to be tested:

$$\text{Covariate}_{i,k} = \alpha_k + \beta_k \text{Treated}_i + \gamma_k \text{Dark } \%_i + \epsilon_{i,k}, \tag{3.16}$$

and then test the hypothesis that all β_k are jointly equal to zero, by performing a χ^2 test. The SUR method allows for contemporaneous correlation between the error terms in the system of equations (Zellner and Theil (1962)). I test the joint significance of β_k for the most obvious covariates (using their pre-treatment average value): log of market capitalization, volume, volatility, and share price. The null hypothesis that all coefficients are jointly equal to zero is strongly rejected (Table 3.A4 in Appendix). That indicates that there exists a discontinuity in some important observable variables (more precisely, volume and share price) around the threshold, preventing the implementation of an RD design. Table 3.A5 (in Appendix), reports the estimated coefficient by RDD with the log of the share price as the dependent variable.

[16] See, for instance: https://ec.europa.eu/info/law/better-regulation/have-your-say/initiatives/1077-Commission-Delegated-Regulation-amending-the-MiFID-2-Delegated-Regulation-with-respect-to-systematic-internaliser-defint/F2136_da

The coefficient is positive and statistically significant at the 5% level, meaning that stocks immediately to the right of the threshold have a significantly higher stock price than stocks immediately to the left of it. As is shown in Section 6, those are the stocks the least impacted by the regulation, as they should have the lowest level of noise trading (Lee et al. (1991), Peress and Schmidt (2019)). A standard RDD estimation would thus underestimate the impact of the regulation.

To overcome the bias that can be induced by the large differences between the two groups, I first implement a propensity score matching procedure, based on baseline covariates, and run a panel regression on the matched sample. The second method augments the standard Difference-in-Differences estimator by including stock-specific weights to make treated and control units comparable, and time-specific weights to make the pre and post-treatment periods comparable, relaxing the parallel trend assumption.[17] This second method focuses on making control and treated units comparable in terms of outcome variables.

3.5 A Pecking Order of Trading Venues

This section develops a "pecking order" analysis of trading venues, based on the response of their market share following a VSTOXX surprise, the most popular European volatility index based on the option prices of STOXX 50 stocks.[18] As this index is forward-looking and option-based, it is unrelated to the contemporaneous choice of stock trading venues. Positive VSTOXX surprises increase the urgency to trade investors through, at least, two channels. It generally translates into a news shock, and it increases the portfolio risk of investors, increasing the utility cost of not trading.

3.5.1 Hypotheses

A "pecking order" analysis requires understanding how each venue type works and how its matching mechanism influences the trade-off between speed of execution and price improvement. Lit venues are characterized by a transparent order book and a continuous matching system. Those order books are generally monitored, in part, by market makers but any trader can be a liquidity provider. We make the hypothesis that they are at the bottom of the pecking

[17] Then, in case the data exhibit substantial trends, the estimator would overweight the periods close to the regulation.

[18] Menkveld et al. (2017) also use earnings announcements and macroeconomic data releases as shocks to the urgency to trade. I chose not to use macroeconomic data releases as my sample covers different countries (including inside and outside the Eurozone). Most earnings announcements at the time were around March 12, 2018. The objective of this section is to test the pecking order in "normal times".

order. Dark pools, on the contrary, do not display their order book, and match buyers and sellers within the European Best Bid Offer (EBBO). They do not guarantee the immediacy of execution but do guarantee a price improvement over traditional lit exchanges; as such, they should rank above lit venues in the pecking order. Auctions are frequent batch auctions: orders are also matched within the EBBO collar, but their periodicity should make them less attractive than dark pools in times of urgency. Systematic Internalisers are a MiFID construct and are operated by investment firms when they match clients' orders on their books, outside regulated or self-regulated trading venues. A key hypothesis (that remains an open question) is that investment firms operating as Systematic Internalisers might reduce their liquidity provision following an immediacy shock, as they are, themselves, likely to be liquidity takers. Finally, Over-the-Counter trading might become less attractive in those market conditions, as search times become more utility costly. It is hard to predict which, of OTC and SI, are at the top of the pecking order.

3.5.2 Urgency Shocks and VARX model

VSTOXX surprises are defined as the residuals of an AR(1) estimated for the daily change in VSTOXX level ($d\text{VSTOXX}_t = \text{VSTOXX}_t - \text{VSTOXX}_{t-1}$):

$$d\text{VSTOXX}_t = \alpha d\text{VSTOXX}_{t-1} + \text{Surprise}_t \tag{3.17}$$

Then I define:

$$\begin{cases} d\text{VSTOXX}_t^+ = \max(0; \text{Surprise}_t) \\ d\text{VSTOXX}_t^- = -\min(0; \text{Surprise}_t) \end{cases}$$

For each stock i and each day t, (logged) trading volumes are aggregated by venue type (lit, dark, auctions, OTC, SI), and arranged into a vector $y_{i,t}$. The panel Vector Autoregression with Exogenous Variables (VARX) model has the following form:

$$y_{i,t} = \alpha_i + \phi y_{i,t-1} + \gamma X_t + \epsilon_{i,t} \tag{3.18}$$

Where order 1 for the VARX process is chosen to minimize the Bayesian Information Criterion (Hayashi, 2000), and X_t is the matrix of exogenous variables. The exogenous variables are the VSTOXX level and $d\text{VSTOXX}^+$.[19] Using the estimated coefficients, I can compute an Impulse Response Function (IRF) for the (logged) trading volume of each venue type. It is

[19]When shocking $d\text{VSTOXX}^+$ in the simulations, I make sure to shock the VSTOXX level accordingly as well.

straightforward to show that the IRF at any period t can be computed as:

$$\text{IRF}_t = \phi \text{IRF}_{t-1} \tag{3.19}$$

starting from

$$\text{IRF}_0 = \frac{\partial y_{i,t}}{\partial X_t} = \gamma. \tag{3.20}$$

Next, I use the estimated IRFs to calculate changes in trading volume for each venue type following an immediacy shock, and the corresponding changes in market shares. Then, I compute the percentage changes in venue types' market share in each period following the VSTOXX surprise. The coefficient estimates from 3.4 and their covariance matrix are used to simulate 10,000 processes, and the confidence intervals are selected at the 2.5 and 97.5 percentiles of the simulations.[20]

3.5.3 Results

Results are presented in Table 3.4. We are interested in the coefficient for dVSTOXX^+, as positive VSTOXX surprises are more likely to contain information than negative ones. As the dependent variables are all logged, the coefficients can be interpreted as sensitivities. As predicted, lit venues gain the most volume following positive VSTOXX surprises, followed by dark venues, auctions, OTC, and SI. The IRF of the market shares are graphically represented in the Appendix (Table 3.A1). The changes in market share changes are presented in Figure 3.5.

The "pecking order" provides an explanation of why lit venues and auctions seem to attract the volumes previously seen in dark pools: the most impatient orders previously sent to dark pools are sent to lit venues after the ban, and the most cost-constrained orders are sent to auctions after MiFID II.

3.6 Impact on Liquidity

This section causally identifies the impact of dark pools on liquidity by using the DVC ban as a quasi-natural experiment. To make the treatment and control groups similar, I first implement a propensity score matching procedure. Then, I run a two-way fixed effect regression on the matched sample. Finally, I implement a Synthetic DiD procedure to confirm the results.

[20]The Covariance matrix is computed by double clustering by stock and time (Petersen, 2009).

3.6.1 Propensity Score Matching

Theory predicts that dark pools alter liquidity by attracting more noise traders than lit venues. This intuition is confirmed by the "pecking order" analysis: as the urgency to trade increases, traders favor lit venues at the expense of dark pools and other trading mechanisms. To properly identify the causal effect of dark pools on liquidity, we have to make sure that our treated and control groups are similar in terms of observable characteristics. I use pre-treatment averages of the stock price, (log) market capitalization, volatility, trading volume, and the level of non-institutional ownership. I also include the country of listing and the country of incorporation fixed effects. The first step is to compute the probability that a stock belongs to the treatment group based on this set of observable characteristics in a logit specification. This allows us to derive a propensity score, the estimated probability that each unit belongs to the treatment group. Figure 3.A2 plots the density of the propensity score for stocks in each group. Then, each treated unit is matched to one or more control units by full matching. Each control unit is assigned a weight, such that a combination of a treated unit and one or several weighted control units creates a "subclass", such that the treated unit is similar, in terms of observable characteristics, to the weighted average of the control units in the same subclass. The dotted line in Figure 3.A2 shows that the propensity score density of (weighted) control units resembles that of the treatment group (solid, red line).

3.6.2 Panel Data Results

A matching procedure allows to eliminate the bias due to differences in observable characteristics between the treated and control groups. In addition, the use of both time and unit fixed effects allows to eliminate bias from unobservable factors that change over time but are constant over entities and it controls for factors that differ across entities but are constant over time. The stock fixed effect allows one to make causal inference, even if treated units exhibit greater liquidity before the treatment.[21] The main econometric setting is:

$$y_{i,t} = \alpha_i + \delta_t + \beta \left(\text{Post March}_t \times \text{Treated}_i\right) + \gamma \mathbf{x}_{i,t} + \epsilon_{i,t}, \tag{3.21}$$

where $y_{i,t}$ will be, alternatively, market shares of trading venue types and liquidity measures. The regression uses the weights estimated in the propensity score matching procedure described above. The matrix of time-varying covariates includes volatility, stock price, (logged)

[21] This argument has been used, for instance, to study the impact of algorithmic trading on liquidity, with the introduction of autoquotes in the New York Stock Exchange (Hendershott et al. (2011)).

market capitalization, and overall trading volume (across all trading venues). All continuous covariates are normalized. $Post\ March_t$ is a dummy equal to one when observations are after March 12, 2018, and zero before. $Treated_i$ is a dummy indicating whether stock i belongs to the treatment group. α_i and δ_t are, respectively, firm and time fixed effects. β is the coefficient of interest, estimating the impact of being suspended from trading in dark pools on the dependent variable. The standard errors are clustered at the subclass (Abadie and Spiess, 2022) and trading venue level.

Where have the dark volumes gone? I first run the regression above with the market shares of the different venue types as dependent variables. Results are reported in Table 3.5. As predicted by the "pecking order", the results confirm that lit venues and auctions have benefited the most from the ban. The coefficient on the interaction term is positive and statistically significant for those two venue types. It reports an increase of 1pp in market share for lit venues and 1.7pp for auctions. The coefficient of the interaction term is not statistically significant from zero in regressions with SI and OTC market shares as dependent variables.
Liquidity Impact. I turn to the liquidity impact of the ban. I run regression 3.21 with the spread and the Amihud ratio as dependent variables. Results are reported in Table 3.6. The results show a strong liquidity improvement following the ban: a decrease in bid-ask spread by between 1.4 basis points, a result statistically significant at the 5% level, and a decrease in price impact by almost 0.1, a result statistically significant at the 1% level. Those coefficients are economically significant: they translate a narrowing of the spread by almost 6% (Column 2) and a decrease of the price impact by 5%. Column 4 indicates that the liquidity improvement is concentrated among the reference lit exchanges, as the weighted average spread on other lit venues is not impacted by the dark pool suspension.

3.6.3 Heterogeneous effects

The model developed in Section 3.2 makes two predictions: suspending the access to dark pools should improve liquidity, and especially so for *i)* volatile stocks, and *ii)* for stocks with high levels of noise trading.

Volatility. In the spirit of Zhu (2014), I define a stock's volatility as the standard deviation of its daily return. I create a triple interaction: $Post\ March_t \times Treated_i \times Volatility_i$, where $Volatility_i$ is stock i's pre-treatment standard deviation of daily returns. Results are reported in Table 3.7.

The estimated coefficient on the triple interaction in Column 1 is negative and statistically significant and indicates that a one standard deviation increase in return volatility decreases the spread for banned stocks by an additional 2bps. Alternatively, the spread decreases by an additional 6% for them (Column 2). Those two results are consistent with Prediction 1.1. Although not significant, the coefficient estimated in Column 3, with the Amihud ratio as the dependent variable, also indicates that more volatile stocks are more impacted by the regulation, in line with Prediction 2.1. However, part of the effect could be driven by the fact that more volatile stocks see a larger increase in the share of lit trading than other treated stocks (Column 5).

Noise trading. I now turn to the cross-sectional analysis of the impact of the regulation. We make the hypothesis that the impact of the suspension on the spread should be larger for stocks with a higher share share of noise trading. Retail ownership is a popular proxy for noise trading (noise trading is more frequent among retail investors). I create a triple interaction: $Post\ March_t \times Treated_i \times Retail_i$ with the level of retail ownership, when available. Table 3.8 reports the estimated coefficients. In these regressions, I use the log of the spread and the log of the lit market share as dependent variables, such that the coefficients can be interpreted as sensitivities. For the spread and the Amihud ratio (Columns 1 and 3), the coefficient on the triple interaction is negative and statistically significant at the 10% level, while the coefficient on the simple interaction $Post\ March_t \times Treated_i$ is not statistically different from zero. This indicates that the effect of the ban is concentrated among stocks with a high level of retail ownership. In Column 3, the dependent variable is the log spread, and the coefficient on the triple interaction indicates that a one standard deviation increase in retail ownership leads to a decrease in spread of 12% (p-value <5%) due to the ban. Those effects are in line with Prediction 1.2, and do not seem to be driven by higher trading volumes, as the coefficient is not statistically significant from zero when we have the (logged or not) lit market share as the dependent variable (Columns 4 and 5). Those results point to the fact that it is the composition of orders, rather than their volume, that drives the liquidity improvement on lit venues following the ban. They tend to confirm the prediction that dark trading alters liquidity by increasing adverse selection in stock exchanges. Finally, the model did not make clear prediction about whether stocks with higher share of noise trading would see a greater decline in price impact. The estimated coefficient in Column 3 seems to indicate that, although it is weakly significant, stocks with more noise trading have a larger decline in Amihud ratio.

3.6.4 Synthetic Difference-in-Differences

I now try to estimate the impact of the DVC mechanism on liquidity and market fragmentation using a Synthetic DiD approach (Arkhangelsky et al. (2021)), a unit and time-weighted version of the standard DiD estimator. The method optimally selects stock-specific weights, to balance pre-treatment outcomes between control and treated units. In addition, it allows to compute time weights so that within the control group, the pre-treatment weighted average of the outcome approximates the post-treatment average. It relaxes the parallel trend assumption by assuming that there exist unit and time weights such that the average treated unit and the weighted average of the control units satisfy the parallel trend assumption. Moreover, it does not need to satisfy it for all periods but only for the averaged post-treatment period and the weighted average of the pre-treatment periods. This method requires using a balanced panel dataset. For each dependent variable (spread, Amihud ratio, lit market share), I select the stocks/date combination with the most available observations.[22]

Results are presented in Table 3.9. The coefficients for the spread and the Amihud ratio are very close to those estimated in the panel regressions. The impact of the DVC mechanism on the market share of the reference lit exchange is greater, indicating an increase by 1.6%, 50% larger than the panel estimate. Again, the regulation seems to have no impact on the volume-weighted average spread based on quotes from lit venues other than the reference exchange. Figures 3.A3, 3.A4, 3.A5, and 3.A6 offer a graphical representation of the Synthetic DiD estimation.

3.7 Conclusion

Technological advances and regulatory changes have permitted the development of Multilateral-Trading-Facilities in Europe. Among them, dark pools have attracted special attention: by removing pre-trade transparency and offering potential price improvement, they are more likely to attract uninformed investors and widen both the spread of the reference lit exchange and the price impact of an order.

However, trying to evaluate the impact of dark trading on liquidity is limited by endogeneity issues. By suspending a large number of stocks from dark trading when their share of trading in the dark is greater than 8%, MiFID II's Double-Volume-Cap mechanism provides an ideal

[22] More specifically, I compute how many stocks have available data on each day. Starting with the day with the highest number of observed data, I add the day with the second highest number of stocks and compute how many stocks are available on both dates. Doing that with all dates in the period, I select the dataset with the most observations (number of days × number of stocks).

framework to identify the effect of dark pool on equity markets' liquidity. This paper shows that suspending stocks from trading in the dark narrows their bid-ask spread and Amihud ratio by 6% and 9% respectively, a result robust across several specifications. Reference lit exchanges and auctions are the trading venue types that attracted the dark volumes, as they are, respectively, above and below dark pools in a "pecking order" of trading venues.
Finally, I document that the liquidity impact of the suspension is concentrated among the most volatile stocks and the stocks with the highest level of retail ownership. To the extent that retail ownership is a good proxy for noise trading, those results are in line with the prediction that dark trading is detrimental to market liquidity through an adverse selection effect.
This paper sheds light on the impact of dark trading on liquidity and investigates the channels through which dark trading is detrimental to market liquidity. Future research could focus on different measures of liquidity as well as other dimensions of market quality.

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Table 3.1: Summary statistics

Variable	Mean	Median	Q1	Q3	SD
i. Characteristics					
Stock Price (EUR)	345.20	43.20	14.20	208.60	862.30
Market Cap (B EUR)	9.60	2.80	1.20	7.60	20.90
Lit volume (main exchange, M EUR)	16.80	5.00	1.50	14.70	33.30
Total Volume (M EUR)	73.90	16.50	4.50	64.30	157.70
Volatility	16.20	14.90	12.30	18.80	5.80
2017 Dark Volume (EUR)	8.40	8.20	5.40	11.30	4.60
ii. Liquidity					
Spread (bps)	22.10	17.50	8.30	29.00	18.80
Average Other Spread (bps)	392.80	257.90	169.30	433.30	436.40
Weighted Average Other Spread (bps)	86.30	46.20	19.70	107.00	116.70
Amihud Ratio	-2.30	-2.60	-4.10	-0.70	2.60
iii. Ownership					
Retail Ownership (when available, %)	40.40	40.00	25.00	50.00	18.20
Non-institutional Ownership (%)	30.80	28.50	17.80	41.20	17.70

Notes: This table displays summary statistics for selected variables. *Lit Volume* is defined as the turnover, in Euros, on the reference lit exchange. *Total Volume* is the total trading volume across all trading venues. *Volatility* and *Amihud Ratio* are defined in the main text. *Spread* is the closing bid-ask spread on the reference lit exchange, while *Average Other Spread* and *Weighted Average Other Spread* are calculated from the closing bid-ask spreads from other lit venues. The averages are calculated from daily data between January 29, 2018 and March 9, 2018. All data, except *Retail Ownership*, are from Refinitiv. *Retail Ownership* is from Orbis.

Table 3.2: Median market share of each venue type (%), by group and period

Group	Period	Lit	Dark	Auction	SI	OTC	Other
Control	Pre	54.80	2.80	8.40	22.90	6.70	1.70
Control	Post	51.60	2.50	8.70	25.20	8.00	1.60
Treated	Pre	45.50	4.60	9.00	28.50	8.30	2.10
Treated	Post	45.70	2.70	10.90	29.70	9.60	1.70

Notes: This table displays median market shares for each venue type by group and period. Venue types are defined by Refinitiv. *Treated* stocks are stocks suspended from dark pools by the DVC mechanism on March 12, 2019. The *Pre* period is from January 29, 2018 to March 9, 2018, and the *Post* period is from March 12, 2018 to April 26, 2018.

Table 3.3: Average liquidity measures by group and period

Group	Period	Spread	Amihud	Lit Volume	Average Other Spread	Weighted Average Other Spread
Control	Pre	26.30	-2.90	22.60	446.20	100.90
Control	Post	26.30	-3.00	20.40	446.30	87.60
Treated	Pre	18.20	-1.60	11.00	347.70	77.50
Treated	Post	17.40	-1.80	11.40	326.50	71.70

Notes: This table displays average liquidity measures by group and period. *Treated* stocks are stocks suspended from dark pools by the DVC mechanism on March 12, 2019. The *Pre* period is from January 29, 2018 to March 9, 2018, and the *Post* period is from March 12, 2018 to April 26, 2018. *Lit Volume* is defined as the turnover, in Euros, on the reference lit exchange. *Spread* is the closing bid-ask spread on the reference lit exchange, while *Average Other Spread* and *Weighted Average Other Spread* are calculated from the closing bid-ask spreads from other lit venues.

Table 3.4: VARX results

Dependent Variables:	Lit volume	Dark volume	Auction volume	OTC volume	SI volume
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
Lagged Lit volume	0.266***	0.165***	0.123***	0.256***	0.228***
	(0.022)	(0.036)	(0.023)	(0.025)	(0.021)
Lagged Dark volume	0.016***	0.131***	0.016***	0.022***	0.031***
	(0.004)	(0.012)	(0.003)	(0.007)	(0.005)
Lagged Auction volume	0.130***	0.142***	0.151***	0.121***	0.189***
	(0.020)	(0.043)	(0.020)	(0.022)	(0.025)
Lagged OTC volume	0.016***	0.020*	0.016**	0.143***	0.051***
	(0.005)	(0.011)	(0.006)	(0.015)	(0.008)
Lagged SI volume	0.036***	0.070***	0.044***	0.078***	0.175***
	(0.010)	(0.021)	(0.009)	(0.016)	(0.016)
VSTOXX	-0.004	-0.009	-0.008	-0.002	0.001
	(0.005)	(0.007)	(0.005)	(0.006)	(0.003)
$dVSTOXX^{+}$	0.045***	0.037***	0.027***	0.004	0.008
	(0.012)	(0.013)	(0.008)	(0.012)	(0.005)
Fixed-effects					
Stock	✓	✓	✓	✓	✓
Fit statistics					
Observations	18,821	18,821	18,821	18,821	18,821
R^2	0.93103	0.74262	0.95071	0.82956	0.91482

Notes: This table reports the estimated coefficients for Equation 3.4. All dependent variables are logged trading volume. Trading venue types are defined by Refinitiv. *VSTOXX* is the option-based volatility index linked to the Stoxx 50 stock index. *$dVSTOXX^{+}$* as the positive and negative surprise changes in the volatility index, computed as the residuals of an AR(1) process. Clustered (Stock & Date) standard-errors in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

Table 3.5: The impact of suspending dark pools on trading venues' market shares

Dependent Variables:	Lit Venues	Dark	Auctions	SI	OTC	Other
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Volatility	-0.948***	0.009	0.159***	-1.358***	-0.478***	2.454***
	(0.193)	(0.073)	(0.060)	(0.163)	(0.089)	(0.204)
Log Market Cap	10.259	-6.220	7.305*	-8.729	-10.551	5.816
	(10.870)	(5.541)	(4.182)	(8.020)	(6.553)	(5.862)
Total Trading Volume	7.223***	0.817***	-5.151***	6.109***	2.865***	-11.963***
	(0.769)	(0.244)	(0.256)	(0.700)	(0.391)	(1.040)
Stock Price	-28.684*	7.293	-6.832	18.872	16.610*	-5.375
	(16.129)	(8.400)	(6.025)	(12.276)	(9.354)	(9.886)
Post × Treated	0.958**	-1.400***	1.661***	0.564	0.103	0.735
	(0.455)	(0.213)	(0.158)	(0.506)	(0.265)	(0.450)
Fixed-effects						
Stock	✓	✓	✓	✓	✓	✓
Time	✓	✓	✓	✓	✓	✓
Fit statistics						
Observations	44,504	32,167	44,499	44,232	43,880	31,888
R^2	0.55466	0.17236	0.51256	0.41508	0.19130	0.74894

Notes: This table reports the estimated coefficients for Equation 3.21. All dependent variables are market shares, in percent of total trading volume. Trading venue types are defined by Refinitiv. *Post* is a dummy equal to one after March 12, 2018. *Treated* is equal to one if a stock is suspended from dark pools by the DVC mechanism from March 12, 2018. The sample period extends from January 29 to April 26, 2018. Cluster-robust standard errors are reported between parenthesis. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.

Table 3.6: The impact of suspending dark pools on liquidity

Dependent Variables:	Spread	Log Spread	Price Impact	Other Spread
Model:	(1)	(2)	(3)	(4)
Variables				
Volatility	1.413***	0.049***	0.016	8.743*
	(0.153)	(0.011)	(0.018)	(4.149)
Log Market Cap	-18.880***	-0.891***	-0.517**	34.616
	(1.856)	(0.093)	(0.195)	(19.665)
Total Trading Volume	-1.898***	-0.081*	-0.603***	-30.719**
	(0.439)	(0.039)	(0.032)	(11.043)
Stock Price	15.773***	0.845***	1.372*	-239.859
	(2.157)	(0.057)	(0.644)	(159.068)
Post × Treated	-1.346**	-0.063*	-0.091***	4.059
	(0.571)	(0.033)	(0.022)	(9.641)
Fixed-effects				
Stock	✓	✓	✓	✓
Time	✓	✓	✓	✓
Fit statistics				
Observations	44,504	44,504	44,504	42,465
R^2	0.43994	0.58096	0.89585	0.49222

Notes: This table reports the estimated coefficients for Equation 3.21. *Price Impact* is measured as the Amihud ratio. *Spread* refers to the bid-ask spread on the reference lit exchange, while *Other Spread* is the volume-weighted average bid-ask spread on other lit venues. *Post* is a dummy equal to one after March 12, 2018. *Treated* is equal to one if a stock is suspended from dark pools by the DVC mechanism from March 12, 2018. The sample period extends from January 29 to April 26, 2018. Cluster-robust standard errors are reported between parenthesis. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.

Table 3.7: The impact of suspending dark pools on liquidity, by level of volatility

Dependent Variables:	Spread	Log Spread	Price Impact	Lit Share	Log Lit Share
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
Log Market Cap	-21.769***	-1.021***	-0.247	16.272***	0.613***
	(1.807)	(0.093)	(0.201)	(2.720)	(0.023)
Stock Price	22.442***	1.085***	0.930	-35.896***	-1.588***
	(2.955)	(0.057)	(0.668)	(6.909)	(0.379)
Total Trading Volume	-0.277	-0.026	-0.599***	6.355**	0.060
	(0.332)	(0.032)	(0.046)	(2.461)	(0.079)
Post × Treated	-1.363**	-0.065	-0.102***	0.931***	-0.002
	(0.571)	(0.038)	(0.023)	(0.291)	(0.038)
Post × Pre-treatment Volatility	2.029*	0.054*	-0.023	-0.590*	-0.045***
	(0.961)	(0.026)	(0.015)	(0.271)	(0.011)
Post × Treated × Pre-treatment Volatility	-2.210**	-0.056*	-0.011	0.234	0.028**
	(0.958)	(0.026)	(0.017)	(0.268)	(0.011)
Fixed-effects					
Stock	✓	✓	✓	✓	✓
Time	✓	✓	✓	✓	✓
Fit statistics					
Observations	44,885	44,885	44,885	44,885	43,865
R^2	0.46348	0.57656	0.89554	0.55575	0.63513

Notes: This table reports the estimated coefficients of a panel regression with a triple interaction. All dependent variables are defined in the main text. *Post* is a dummy equal to one after March 12, 2018. *Treated* is equal to one if a stock is suspended from dark pools by the DVC mechanism from March 12, 2018. *Mkt Cap* is logged. *Turnover* is the overall trading volume across all trading venues for a stock. *Retail* is the level of retail ownership, from Orbis. The sample period extends from January 29 to April 26, 2018. Cluster-robust standard errors are reported between parenthesis. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

Table 3.8: The impact of suspending dark pools on liquidity, by level of retail ownership

Dependent Variables:	Spread	Log Spread	Price Impact	Lit Share	Log Lit Share
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
Volatility	2.404***	0.056***	-0.005	-0.484	-0.003
	(0.564)	(0.013)	(0.017)	(0.302)	(0.034)
Log Market Cap	223.573*	6.518***	-6.557	-82.737	-13.109
	(108.402)	(1.583)	(5.234)	(61.844)	(12.984)
Total Trading Volume	-4.671	-0.102	-0.544***	5.054*	0.140
	(3.434)	(0.090)	(0.058)	(2.326)	(0.235)
Stock Price	-318.789*	-9.346***	10.341	125.697	18.634
	(151.921)	(2.322)	(7.717)	(92.752)	(18.141)
Post × Treated	-4.115	-0.087	-0.006	1.287**	-0.054
	(2.739)	(0.076)	(0.071)	(0.546)	(0.105)
Post × Retail Ownership	2.100	0.046	0.105	-0.035	0.113
	(2.158)	(0.052)	(0.084)	(0.491)	(0.149)
Post × Treated × Retail Ownership	-4.803*	-0.129**	-0.223*	0.931	-0.060
	(2.507)	(0.054)	(0.106)	(0.551)	(0.149)
Fixed-effects					
Stock	✓	✓	✓	✓	✓
Time	✓	✓	✓	✓	✓
Fit statistics					
Observations	8,094	8,094	8,094	8,094	8,094
R^2	0.41023	0.54927	0.82202	0.58638	0.45583

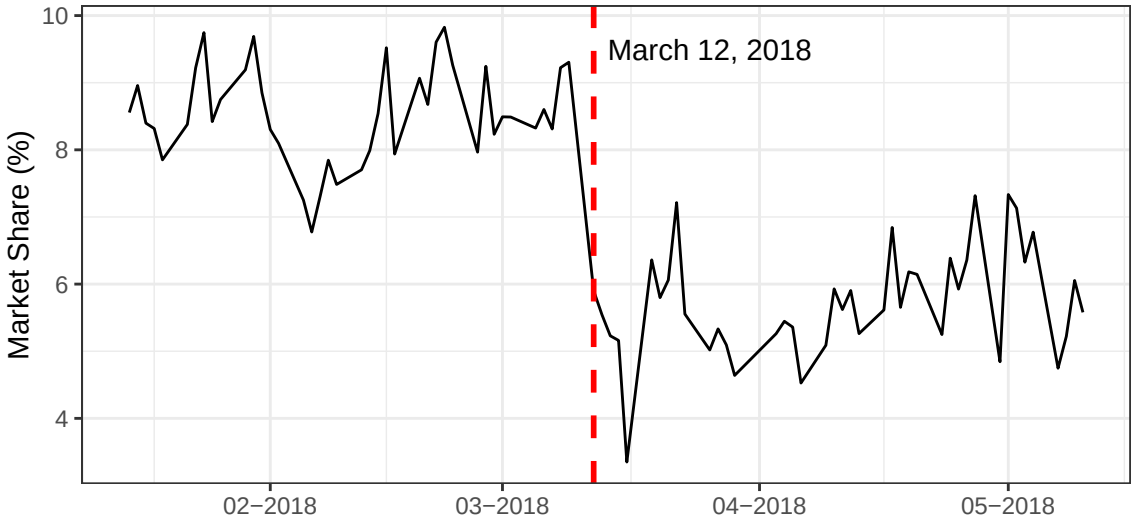
Notes: This table reports the estimated coefficients of a panel regression with a triple interaction. All dependent variables are defined in the main text. *Post* is a dummy equal to one after March 12, 2018. *Treated* is equal to one if a stock is suspended from dark pools by the DVC mechanism from March 12, 2018. *Mkt Cap* is logged. *Turnover* is the overall trading volume across all trading venues for a stock. *Retail* is the level of retail ownership, from Orbis. The sample period extends from January 29 to April 26, 2018. Cluster-robust standard errors are reported between parenthesis. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

Table 3.9: Synthetic DiD estimates

Dependent Variables:	Spread	Log Spread	Price Impact	Lit Share
Model:	(1)	(2)	(3)	(4)
Variables				
Post × Treated	-1.694***	-0.046***	-0.081	1.590***
	(0.397)	(0.013)	(0.043)	(0.303)
Fixed-effects				
Stock	✓	✓	✓	✓
Time	✓	✓	✓	✓
Fit statistics				
Observations	64,141	64,141	17,820	46,312

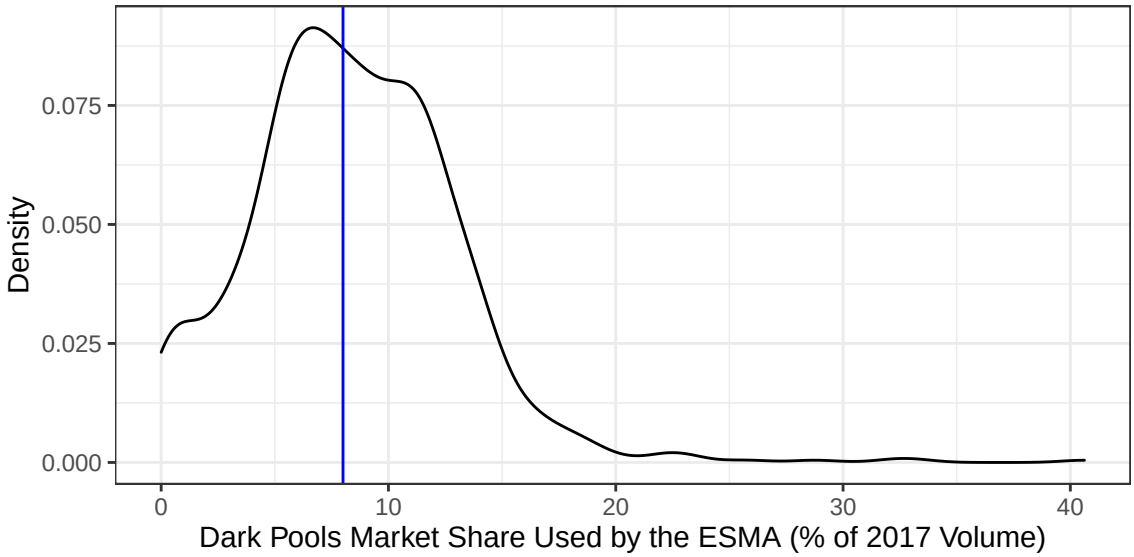
Notes: This table reports the estimated coefficients from a Synthetic Difference in Differences (Arkhangelsky et al., 2021) of different liquidity measures (Columns 1 to 3), or the market share of the reference lit exchange. *Spread* refers to the bid-ask spread on the reference lit exchange. *Price Impact* is measured as the Amihud ratio. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

Figure 3.1: The Evolution of Dark Pools' Market Share.



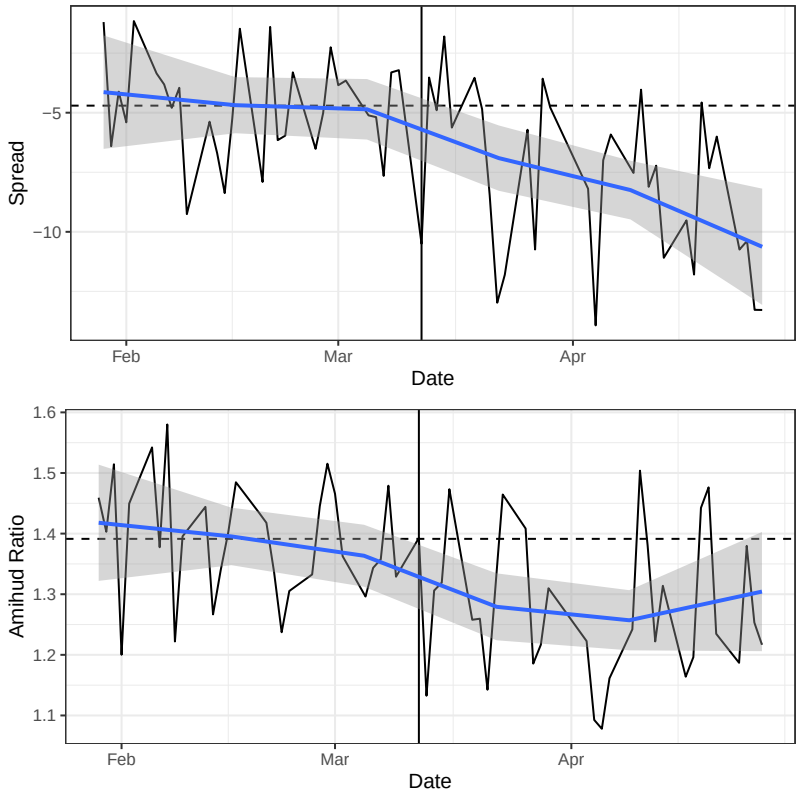
Notes: The figure displays the daily market share of dark pools in Europe (% of notional volume). The red line shows the first wave of suspensions from dark pools (March 12, 2018). The period covered spans from January 11 to May 11, 2018. Data: CBOE Europe Global Markets

Figure 3.2: Density of the Share of Dark trading



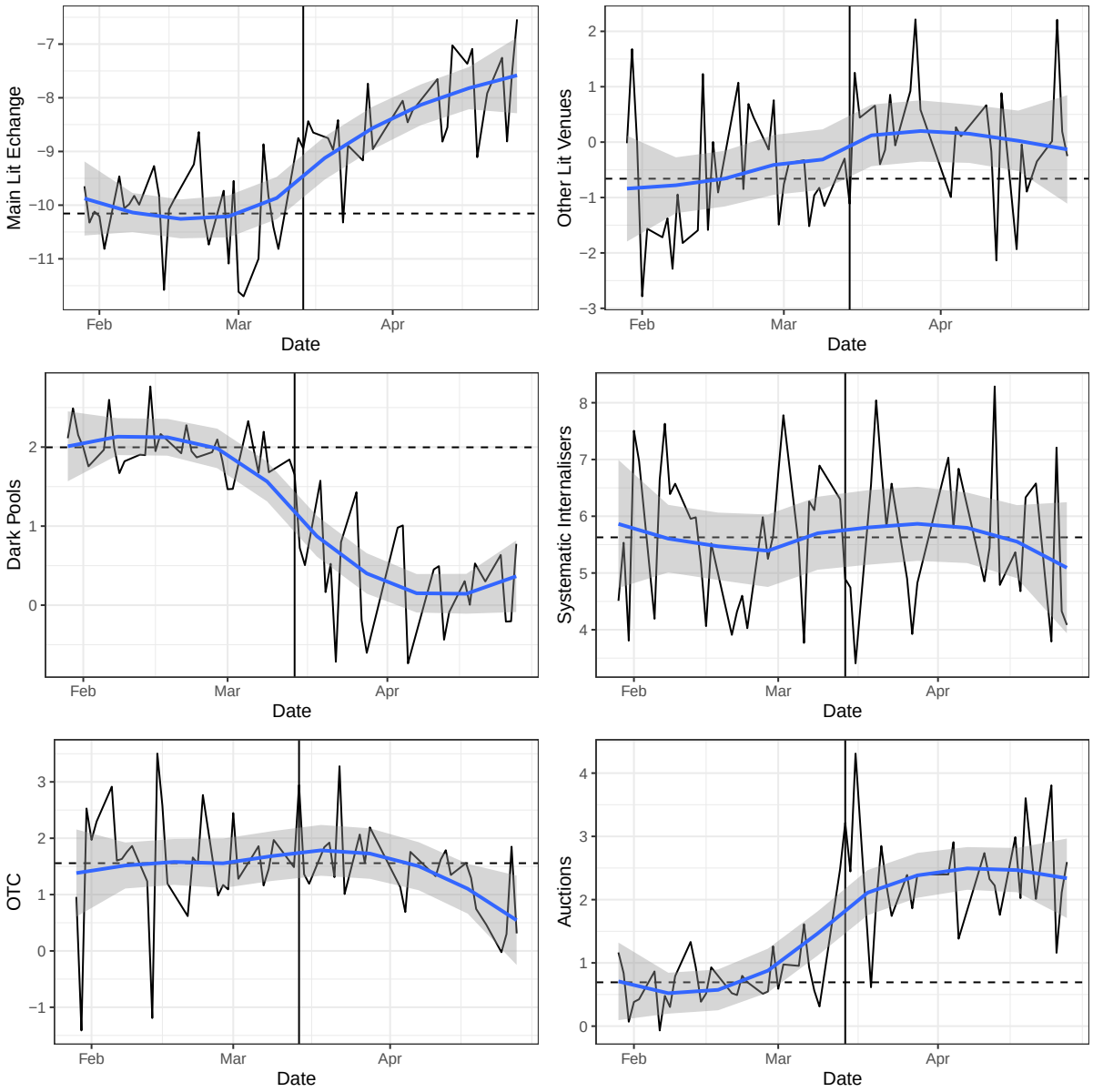
Notes: The figure displays the distribution of the share of dark trading considered by the ESMA for the first wave of bans. The vertical bar represents the threshold of 8%. Stocks above the threshold are suspended on March 12, 2018. Data: ESMA Double-Volume-Cap files from January and February 2018.

Figure 3.3: Difference in average liquidity measures around the ban



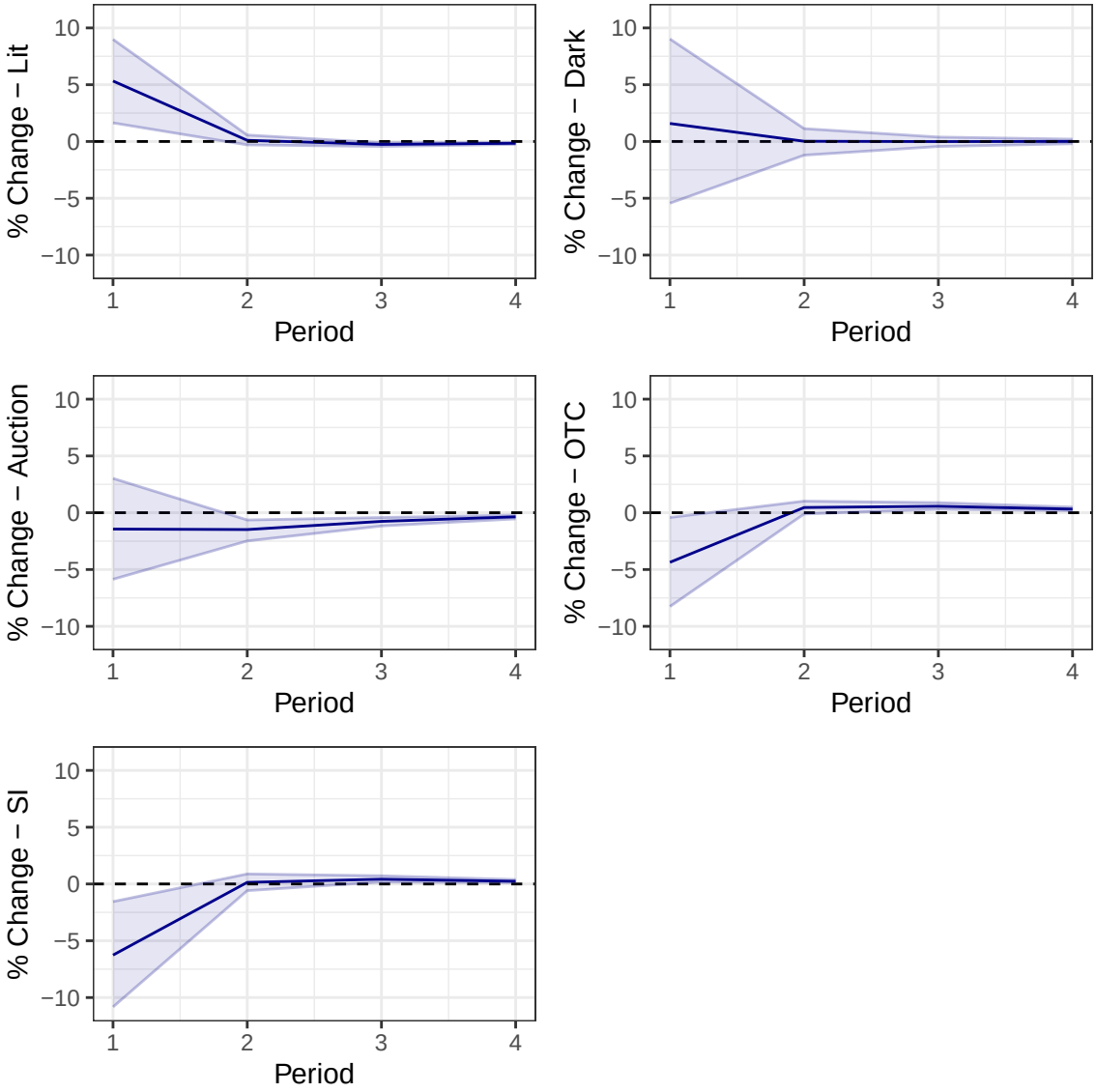
Notes: The figure displays the daily difference in average liquidity measures between treated and control groups. Trading venue types are defined by Refinitiv. The sample period is from January 29, 2018, to April 26, 2018. The vertical line represents the implementation of the DVC mechanism (March 12, 2018), and the horizontal dashed line represents the pre-treatment average difference. The blue line is a rolling 5-day moving average, and the shaded area is the 95% confidence interval for the moving average. *Spread* is the closing bid-ask spread from the reference lit exchange. *Amihud Ratio* is defined in the main text.

Figure 3.4: Difference in average market share of venue types around the ban



Notes: The figure displays the daily difference in average market share between treated and control groups. Trading venue types are defined by Refinitiv. The sample period is from January 29, 2018, to April 26, 2018. The vertical line represents the implementation of the DVC mechanism (March 12, 2018), and the horizontal dashed line represents the pre-treatment average difference. The blue line is a rolling 5-day moving average, and the shaded area is the 95% confidence interval for the moving average.

Figure 3.5: Market share change following a VSTOXX surprise



Notes: The figure displays the difference in percentage change in market share between trading venue types, following a VSTOXX surprise. The change in market share is simulated using the estimated coefficients of a VARX model (Equation 3.4). The confidence bounds are selected at the 0.5 and 99.5 percentiles of 10,000 simulations. Period 1 corresponds to the shock.

Appendix to Chapter 3: Omitted Tables and Figures

Table 3.A1: Sample Selection Procedure

Criterion (as of March 7, 2018)	Number of ISIN
All securities reported by the ESMA	25,336
Liquid (ESMA file based on 2017 data) shares	1,485
2017 EU-wide volume greater than €5 mln	1,479
Suspended at EU level or not at all, until May 2018	1,458
Available on Datastream	1,394
RCA* in BE, DE, DK, ES, FI, FR, GB, IT, NL, PL, SE	1,332
Company HQ and listing stock exchange in the EU	1,142
No ESMA mistake	1,096
At least 2/3 of observations are non-zero and Price > €0.5	1,055
Available data in Market Share Reporter	918
Primary issue and quoted in EUR, CHEF, GBP, PLN or SEK	865

Notes: This table reports the sample selection procedure, from the 25,336 securities reported in the January and February ESMA DVC files. ** RCA: Relevant Competent Authority (national regulator)*

Table 3.A2: Listing Countries of Stocks in the Sample

Country of Exchange	Number of Stocks
Belgium	32
Denmark	33
Finland	27
France	115
Germany	133
Italy	81
Luxembourg	1
Netherlands	47
Poland	25
Spain	55
Sweden	79
United Kingdom	237

Notes: This table reports the listing for each of the 865 stocks in the sample (data from Refinitiv).

Table 3.A3: Economic Sector of Stocks in the Sample

Sector	Number of Stocks
Academic & Educational Services	1
Basic Materials	76
Consumer Cyclicals	151
Consumer Non-Cyclicals	58
Energy	31
Financials	126
Healthcare	76
Industrials	175
Real Estate	52
Technology	89
Utilities	30

This table reports the economic sector for each of the 865 stocks in the sample (data from Refinitiv).

Table 3.A4: Linear Hypothesis Test (χ^2 statistic of a Wald test)

Hypothesis:	
Volume:	$\beta^{Treated} = 0$
log(Mkt cap):	$\beta^{Treated} = 0$
Volatility:	$\beta^{Treated} = 0$
Share Price:	$\beta^{Treated} = 0$
Model 1:	*Restricted Model*
Model 2:	SUR

	Res. DF	DF	χ^2	Pr(>χ^2)
1	97686			
2	97682	4	1485.26	0.0000

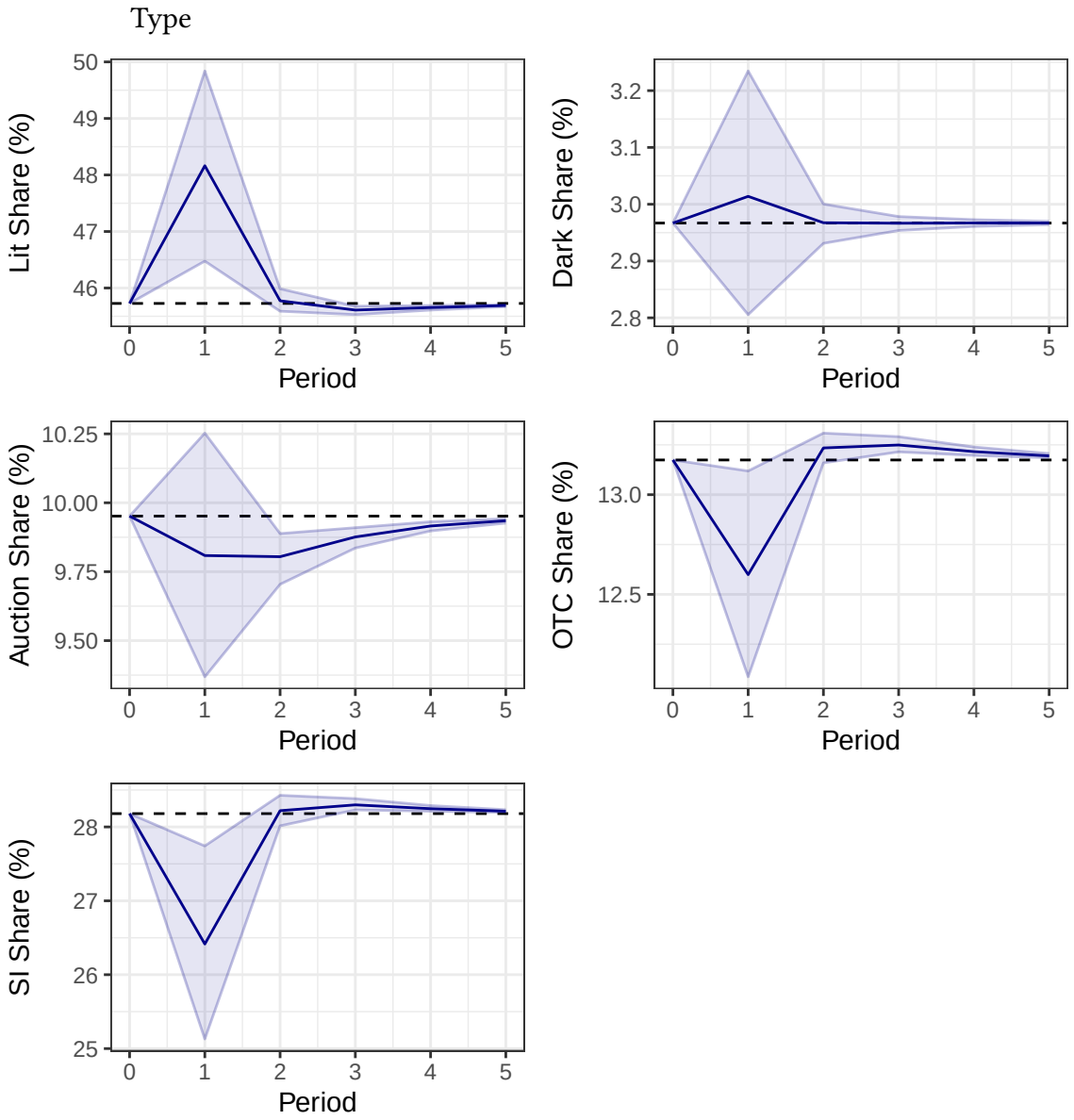
This table reports the result of a Wald test, where the hypothesis is that all coefficients on *Suspended* from the SUR (table above) are jointly equal to zero.

Table 3.A5: Regression Discontinuity Design: log of the Stock Price

Stat	Type	Value
Coef	Local-Linear	0.858
SE	Local-Linear	0.383
t-stat	Local-Linear	2.236
CI	Local-Linear	(0.106,1.609)
Coef	Robust	1.005
SE	Robust	0.445
t-stat	Robust	2.257
CI	Robust	(0.132,1.878)
Bandwidth	–	(1.833,1.833)
Nobs	–	(146,138)
Polynomial Order	–	1

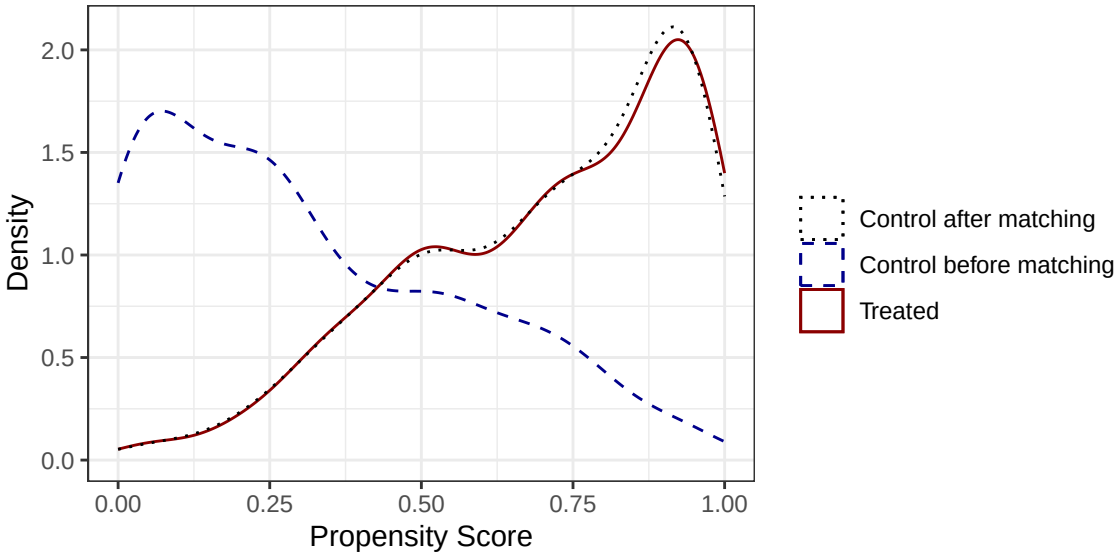
Notes: This table displays the estimated coefficient in a Regression Discontinuity Design. The dependent variable is the log of the average stock price, and the running variable is the 2017 share of dark trading calculated by the ESMA. The cutoff point is at 8%. Estimation details can be found in Calonico et al. (2014).

Figure 3.A1: Impulse Response Function following a VSTOXX surprise, by Trading Venue



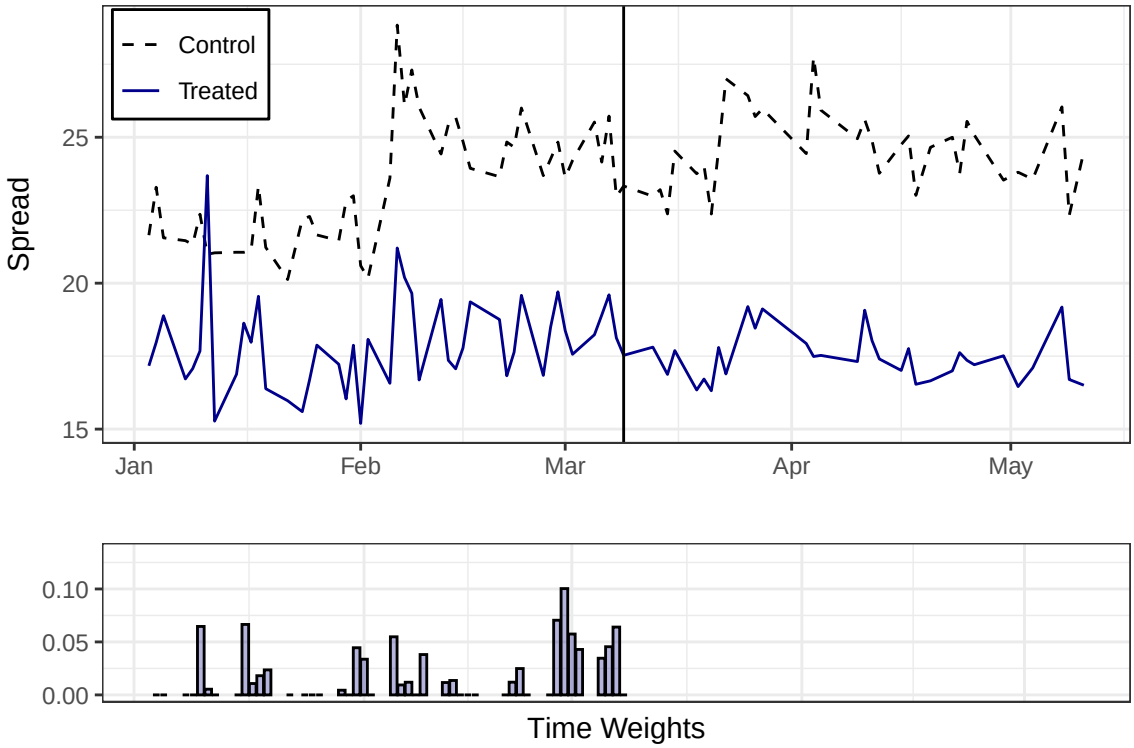
Notes: This figure displays the estimated coefficients from an event study with a firm's voice pressure as the dependent variable, and the interaction between a time dummy and the indirect exposure to Natixis through voice funds as of Q1 18 as the independent variable. The figure shows that funds with high exposure to Natixis-owned voice funds saw a decrease in their voice pressure when Natixis suffered trading losses in 2018. For instance, if Natixis owns 10% of a voice fund that owns 10% of firm n's equity, firm n's voice pressure is expected to decrease by 0.5pp after Natixis' trading losses. The regression also includes firm and quarter fixed effects. The standard-errors used to compute the 95% confidence intervals are clustered at the firm level. The sample covers 646 US firms with high indirect exposure to Natixis.

Figure 3.A2: Propensity score density before and after matching



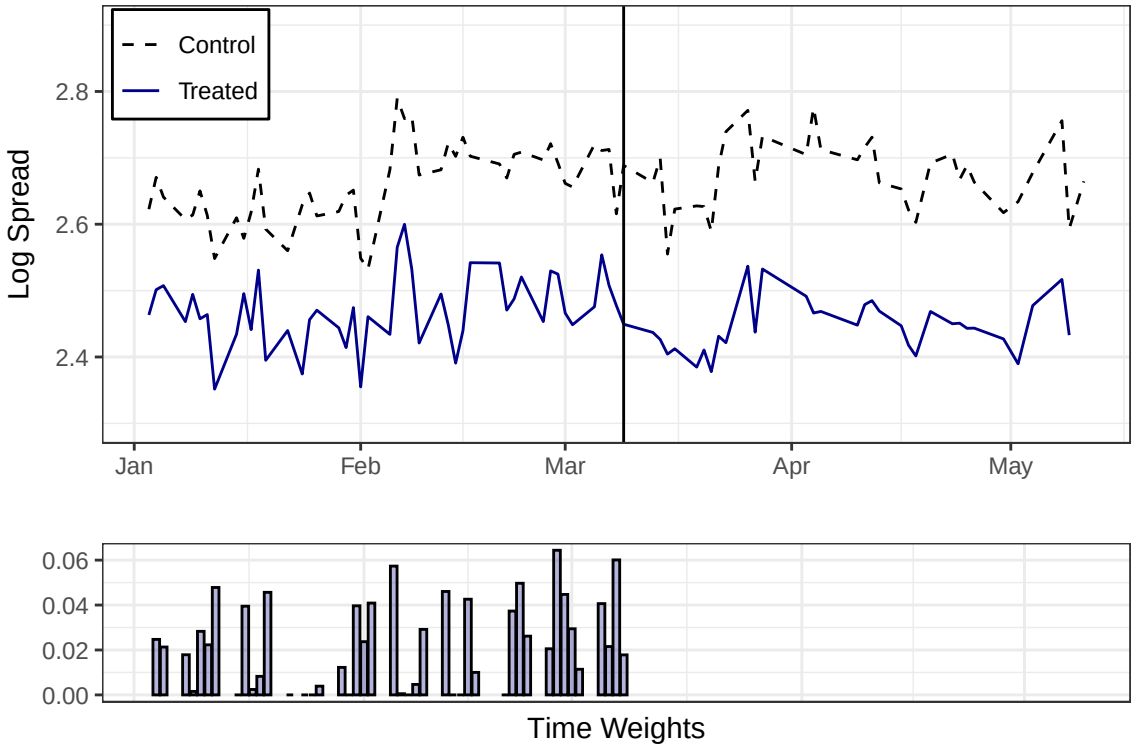
Notes: This figure plots the probability density function of the propensity score (predicted probability of being in the treatment group, based on observable covariates) for treated stocks (solid, red line), control stocks (dashed, blue line), and control stocks after matching (dotted, black line). The propensity score is based on a logit regression of a dummy indicating whether a stock belongs in the treatment group on the stock's pre-treatment average (logged) market capitalization, stock price, volatility, trading volume, and countries of exchange and incorporation. Data from Refinitiv.

Figure 3.A3: Synthetic DiD Estimate: Spread



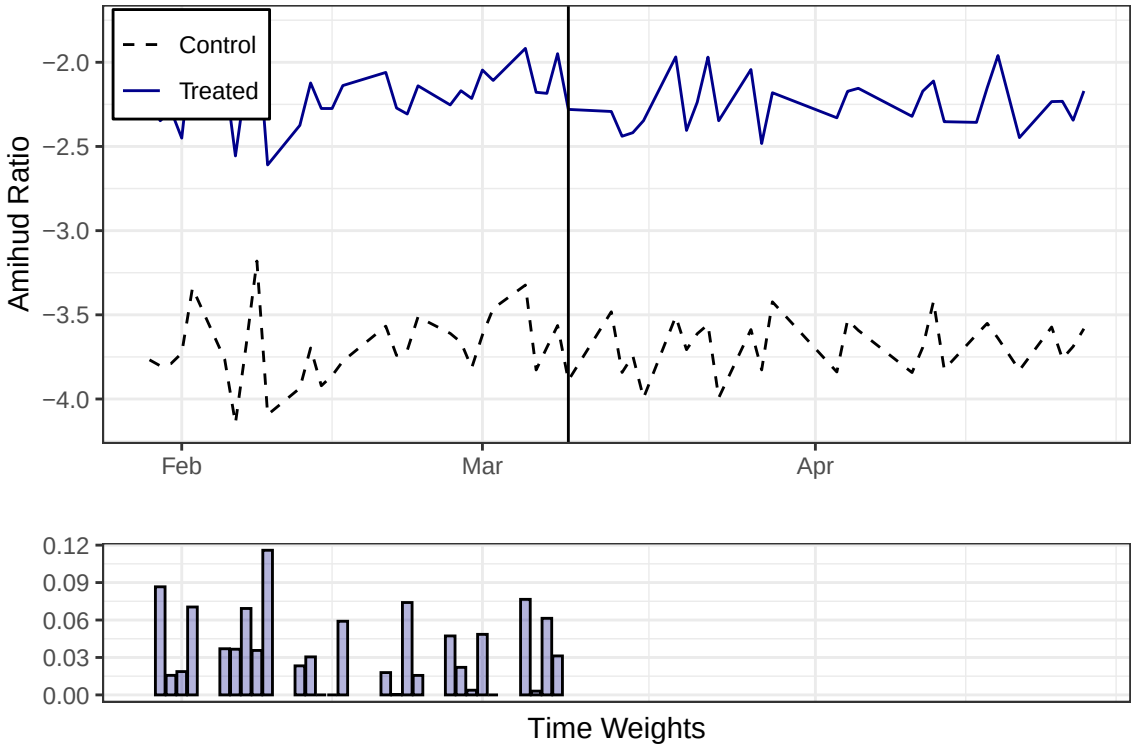
Notes: This figure displays the Synthetic DiD estimate, with the spread as the dependent variable. The histogram along the X-axis represents the time weights assigned to each day. The black arrow represents the estimated coefficient. The sample period covers January 3, 2018 to May 11, 2018.

Figure 3.A4: Synthetic DiD Estimate: Log Spread



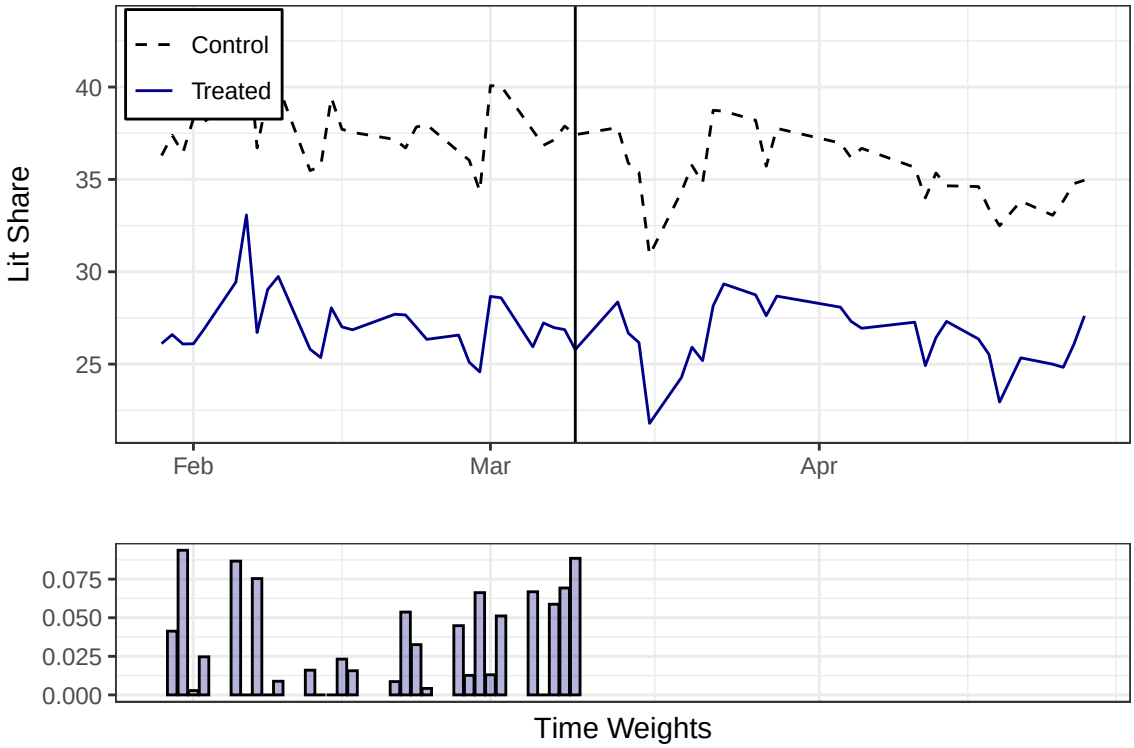
Notes: This figure displays the Synthetic DiD estimate, with the logged spread as the dependent variable. The histogram along the X-axis represents the time weights assigned to each day. The black arrow represents the estimated coefficient. The sample period covers January 3, 2018 to May 11, 2018.

Figure 3.A5: Synthetic DiD Estimate: Amihud Ratio



Notes: This figure displays the Synthetic DiD estimate, with the Amihud ratio as the dependent variable. The histogram along the X-axis represents the time weights assigned to each day. The black arrow represents the estimated coefficient. The sample period covers January 3, 2018 to May 11, 2018.

Figure 3.A6: Synthetic DiD Estimate: Reference Lit Exchange Market Share



Notes: This figure displays the Synthetic DiD estimate, with the market share of the reference lit exchange as the dependent variable. The histogram along the X-axis represents the time weights assigned to each day. The black arrow represents the estimated coefficient. The sample period covers January 29, 2018 to April 26, 2018.

Résumé en Français

Les marchés financiers ont connu des changements structurels profonds au cours des deux dernières décennies. La finance durable attire de plus en plus l'attention des investisseurs (institutionnels et particuliers), des politiciens et des entreprises. Les deux premiers chapitres de cette thèse examinent l'impact des investisseurs socialement responsables sur les décisions des entreprises et le coût que ces décisions représentent pour les autres actionnaires. Simultanément, les cadres réglementaires régissant les lieux de négociation en Europe ont connu une évolution significative pour garantir la transparence, l'équité et la stabilité des marchés financiers. La troisième partie de cette thèse évalue comment la limitation des *dark pools* (plateformes de négociation opaques) a impacté la fragmentation du marché et la liquidité.

Les investisseurs motivés par les critères ESG (Environnementaux, Sociaux et de Gouvernance) devraient-ils éliminer les entreprises non responsables de leur portefeuille, ou devraient-ils plutôt investir en elles et s'engager avec la direction ? Le premier chapitre évalue l'efficacité de ces stratégies de *sortie* (désinvestissement) et de *voix* (engagement) et révèle les conditions dans lesquelles chaque stratégie est la plus impactante. La première contribution de l'article est de créer une mesure des pressions de sortie et de voix pour les entreprises américaines de 2013 à 2020. Je classe les fonds communs de placement américains le long des dimensions de sortie et de voix, en fonction de la composition de leur portefeuille et de leurs votes. Je crée les mesures au niveau de l'entreprise en fonction du pourcentage de capitaux propres détenus par les fonds de sortie et de voix. Ensuite, j'utilise des variations exogènes de ces pressions de sortie et de voix pour identifier de manière causale l'effet de chaque stratégie sur les efforts prosociaux des entreprises. Mon premier résultat est qu'en général, seule la voix est efficace. La deuxième contribution de l'article est de révéler les conditions dans lesquelles chaque stratégie est la plus impactante. L'effet de la voix est plus fort lorsque les administrateurs du conseil cherchent à être réélus et la sortie ne fonctionne que lorsque le PDG détient de nombreuses actions dans son entreprise. La principale conclusion de l'article est que les cadres et les administrateurs répondent aux demandes de leurs actionnaires en matière de

prosocialité uniquement lorsqu'ils ont des incitations personnelles à le faire.

Mais qu'est-ce qui motive les actionnaires à devenir des activistes prosociaux ? Dans le deuxième chapitre, écrit avec Michele Fioretti et Simon C. Smith, nous montrons que de grands investisseurs individuels (comme d'anciens PDG ou fondateurs) poussent pour des actions prosociales visibles et coûteuses lorsque leur entreprise est sous les feux des projecteurs médiatiques. Pour le montrer, nous exploitons les périodes des Assemblées Générales Annuelles (AGA) : c'est une période où les décisions des entreprises ont plus de publicité. La période de l'AGA est la même chaque année, elle est donc exogène par rapport aux événements qui augmentent la demande de prosocialité de la société. Par exemple, nous montrons que les entreprises ayant une AGA et de grands actionnaires individuels sont plus susceptibles de faire des dons au début de la Covid, ou plus susceptibles de couper les liens commerciaux avec les entreprises russes juste après l'invasion de l'Ukraine. Nous interprétons ce résultat comme reflétant les préoccupations d'image de ces actionnaires, car la plupart d'entre eux sont facilement associés à une entreprise. Les actionnaires institutionnels ont tendance à s'opposer à ces actions, car ils n'ont pas de gains d'image similaires. Nous constatons qu'après une action prosociale, leur score de recherche Google augmente de 50%, tandis que celui des actionnaires institutionnels reste stable. Enfin, nous montrons que la recherche de la valeur de ces actionnaires est coûteuse pour les autres : de telles décisions diminuent les bénéfices de 1 à 3%.

Le troisième chapitre examine si nous devrions réglementer les *dark pools* (marchés non transparents avant la négociation). Cet article étudie l'impact d'une réglementation européenne (le mécanisme *Double-Volume-Cap* de MiFID II) limitant l'utilisation des dark pools sur la fragmentation du marché et la liquidité. Ce méchanisme dit que si plus de 8% du volume de négociation d'une action s'est produit dans des dark pools au cours de l'année écoulée, l'action ne peut pas y être négociée pour les 6 mois suivants. Je montre que les volumes des dark pools des actions suspendues sont redirigés vers des plateformes *lit* (transparentes) et les enchères périodiques, conformément à un "ordre hiérarchique" des lieux de négociation. La liquidité s'améliore considérablement sur les bourses d'actions –par rapport aux actions similaires non affectées par l'interdiction– et l'effet est concentré sur les actions avec un niveau élevé de trading non-informé. Ces résultats confirment la prédiction théorique selon laquelle les dark pools heurtent la liquidité en augmentant le risque de sélection adverse sur les marchés boursiers.

Chapitre 1 | Sortie ou Voix ? Désinvestissement, Activisme et Responsabilité Sociale des Entreprises

Plus de 5 000 investisseurs institutionnels, représentant 121 billions de dollars d'actifs sous gestion, ont signé les Principes pour l'Investissement Responsable de l'ONU.[23] Mais comment peuvent-ils exercer une pression sur les entreprises pour qu'elles adoptent des comportements plus socialement responsables ? Dans ses lettres de 2020 et 2021 aux PDG, Larry Fink (PDG de BlackRock) a invité les administrateurs et les dirigeants à réfléchir à l'impact croissant de l'investissement responsable sur le prix des actions de leur entreprise. Il a averti que les entreprises qui n'adoptent pas des pratiques commerciales plus durables devront supporter un coût du capital plus élevé à l'avenir. Ces déclarations résument la menace de *sortie*:[24] confrontées à un désinvestissement potentiel de la part de leurs actionnaires, les entreprises doivent agir de manière plus socialement responsable pour maintenir leur cours de bourse actuel élevé et être en mesure de lever des fonds à faible coût à l'avenir. D'autre part, Fink a également affirmé que BlackRock voterait contre la direction et les administrateurs lorsqu'ils ne progresseraient pas suffisamment sur les questions de durabilité. C'est une façon dont les investisseurs activistes utilisent leur *voix* : ils poussent au changement au sein des entreprises de leur portefeuille en menaçant d'utiliser leur pouvoir de vote. Les entreprises répondent-elles à ces pressions de sortie et de voix ? Dans quelles conditions ?

Cet article examine si les stratégies de sortie et de voix peuvent promouvoir les efforts pro-sociaux en exploitant un nouveau canal de causalité : les préoccupations financières et de carrière de la direction de l'entreprise. Les actionnaires sortants menacent la rémunération des PDG via leur exposition personnelle au cours de l'action de leur entreprise, et les actionnaires activistes menacent la réélection des administrateurs par leurs votes. Les cadres et les administrateurs ont donc des incitations *personnelles* à répondre aux pressions de sortie et de voix. Ce canal spécifique fournirait une alternative au canal du coût du capital pour la sortie (Berk and van Binsbergen, 2021), et pourrait expliquer pourquoi certaines campagnes activistes motivées par les critères ESG sont couronnées de succès (par exemple, Naaraayanan et al., 2021). Pourtant, une évaluation empirique de ces mécanismes rencontre au moins trois défis : *i)* mesurer les pressions de sortie et de voix auxquelles les entreprises sont confrontées, *ii)* trouver des variations exogènes de ces pressions, et *iii)* trouver un proxy pour les efforts de RSE des entreprises.

Cet article apporte deux contributions principales. La première contribution est de dévelop-

[23]Rapport Annuel 2023 de l'UN PRI.

[24]En suivant la terminologie de Hirschman (1970).

per une nouvelle classification des fonds communs de placement américains comme étant sortants, voix, les deux, ou rien. Cette classification trimestrielle couvre près de 2 000 fonds entre 2013 et 2020. Elle me permet de construire une mesure au niveau de l'entreprise des pressions de sortie et de voix, basée sur le pourcentage de capitaux propres détenus par des fonds de sortie et de voix. Ensuite, j'utilise de grands rachats de fonds comme chocs plausiblement exogènes aux pressions de sortie et de voix pour identifier l'impact de chaque stratégie sur les efforts de RSE des entreprises américaines cotées en bourse, tel que le nombre de controverses sociales rapportées par les médias.[25] La deuxième contribution de l'article est d'évaluer l'efficacité de chaque stratégie et de découvrir les conditions dans lesquelles elles sont les plus impactantes.

Je commence par identifier les *fonds de sortie* en utilisant des données sur les positions de portefeuille. J'identifie les fonds ayant une préférence pour les actions pro-sociales en appliquant le cadre de Koijen and Yogo (2019). Plus précisément, à chaque trimestre, je régresse le poids de chaque action dans le portefeuille d'un fond sur ses caractéristiques financières et ses scores environnementaux, sociaux et de gouvernance. Le coefficient sur le score social (β_S) indique si, toutes choses égales par ailleurs, un fond investit davantage dans des actions avec un niveau plus élevé de RSE. Ce coefficient est corrélé à une classification de fonds basée sur les noms. À chaque trimestre donné, je définis comme un fond de sortie tout fond non-indiciel avec un β_S positif.[26] La part des fonds de sortie parmi les fonds non-indiciels est passée de 32% en 2013 à 45% en 2018. Pour chaque entreprise à chaque trimestre, je construis une mesure de la *menace de sortie* que l'entreprise subit de la part de ses actionnaires de fonds de sortie, comme la part de son capital détenu par des fonds de sortie.

J'identifie les *fonds de voix* en utilisant leurs votes aux Assemblées Générales Annuelles (AGA) des entreprises de leur portefeuille. En rassemblant tous les votes des fonds à partir du site web de la Securities and Exchange Commission, je me concentre sur les résolutions portées par les actionnaires relatives aux questions sociales qui sont opposées par la direction. Le score de voix d'un fond à chaque trimestre est le pourcentage de fois où sa société de fonds a voté en faveur de ces résolutions au cours des quatre trimestres précédents. Je constate que la propension à voter en faveur des résolutions liées à la RSE augmente au fil de ma période d'étude et que la plupart des fonds votent soit toujours en faveur, soit toujours contre de telles

[25]Je me concentre sur la dimension *sociale* des externalités des entreprises, car la plupart des votes liés aux critères ESG qui reflètent un désaccord entre les actionnaires et la direction tombent dans la catégorie "S". De plus, les fonds qui désinvestissent des entreprises aux normes environnementales faibles désinvestissent généralement de secteurs entiers (par exemple, les fonds "sans énergies fossiles") plutôt que d'actions individuelles. Enfin, les efforts pro-sociaux des entreprises sont plus comparables entre les sociétés et les secteurs que leurs efforts environnementaux.

[26]Les fonds indiciels, par définition, ne peuvent pas utiliser la menace de sortie.

propositions. Pour tester la corrélation du score de voix avec d'autres proxies, je montre que les participants à l'initiative "Advance" des Principles for Responsible Investment, par laquelle les investisseurs agissent sur les questions sociales au sein des entreprises de leur portefeuille, ont un score de voix significativement plus élevé que les autres. Je crée une mesure de la pression de voix au niveau de l'entreprise comme la part du capital détenu par des fonds avec un score de voix supérieur à 85% (c'est-à-dire au-dessus du pourcentage de recommandations favorables des conseillers en vote sur le même ensemble de résolutions).

Ensuite, je développe un cadre portable pour identifier l'influence des fonds sur les politiques des entreprises. Comme la composition des actionnaires d'une entreprise est endogène, j'identifie causalement l'impact de chaque stratégie sur les efforts de RSE en exploitant des changements plausiblement exogènes dans l'influence des fonds dus à de grands rachats de fonds. L'idée est que lorsque les fonds sont contraints de vendre certains de leurs actifs, ils ont moins de pouvoir pour exercer leur menace de sortie ou leur voix. Pour chaque entreprise à chaque trimestre, je calcule le pourcentage hypothétique de son capital vendu par des fonds de sortie et de voix en raison de grands rachats, comme si les fonds liquidaient leurs actifs de manière proportionnelle. J'utilise d'abord ces chocs dans un design d'étude d'événements. Ensuite, dans l'esprit des instruments shift-share (Borusyak et al., 2022), j'instrumente les changements dans l'exposition des entreprises à la sortie et à la voix des fonds en utilisant ces grands rachats et j'estime leur impact sur le comportement futur des entreprises.

Je mesure les efforts de RSE des entreprises en fonction des controverses sociales publiées dans les médias. Ce sont ma mesure préférée de la RSE car elles sont observables à haute fréquence et permettent d'identifier la date du comportement sous-jacent. De plus, elles reflètent toutes les dimensions de la RSE, même celles qui sont difficiles à mesurer comme la culture d'entreprise. Enfin, elles sont publiquement observables et déclenchent donc de fortes réactions des investisseurs sous forme de rendements anormaux négatifs et de rotations managériales. C'est précisément la crainte de telles punitions qui peut inciter la direction de l'entreprise à agir en réponse aux pressions de sortie et de voix. Lorsqu'une controverse survient, les fonds de sortie — et non les autres — vendent l'action, et les rotations managériales sont concentrées parmi les entreprises avec une forte propriété de voix.

Mon premier résultat est que, en général, seule la voix est efficace pour promouvoir les efforts pro-sociaux. Lorsque les fonds de voix sont contraints de vendre 1% du capital d'une entreprise, la probabilité que l'entreprise soit confrontée à une controverse augmente de 10 à 20%. Ce résultat est cohérent avec la prédiction théorique de Broccardo et al. (2022), et est robuste à plusieurs spécifications et classifications alternatives des fonds de sortie et de voix. Le résultat n'est pas causé par un changement dans la couverture médiatique : le nombre de

nouvelles non liées à l'ESG n'est pas impacté par les changements dans les pressions de sortie et de voix. De plus, le résultat est maintenu lorsque l'on utilise des mesures alternatives de controverses telles que les campagnes des ONG, ou des mesures positives de RSE telles que les scores ESG, les dons de bienfaisance et la diversité des genres au conseil d'administration.

Je valide ce résultat en exploitant un expérience naturelle saillante où la motivation derrière de grands rachats de fonds peut être identifiée. En 2018, la banque d'investissement française Natixis a rapporté plus de 300 millions de dollars de pertes non récurrentes dues à des positions dérivées pariant sur la hausse de l'indice boursier principal de la Corée du Sud. Alors que l'indice chutait de juin à décembre 2018, Natixis a réduit de près de 50% ses avoirs dans les fonds d'actions américains. J'exploite l'hétérogénéité de l'exposition des fonds à Natixis avant les pertes comme un choc à l'influence des fonds. Les entreprises fortement exposées aux fonds de voix appartenant à Natixis ont vu une forte diminution de la pression de voix après les pertes de trading et une augmentation subséquente des controverses.

Mon deuxième résultat est que l'effet nul inconditionnel de la sortie masque une certaine hétérogénéité intéressante. Je constate que les entreprises avec une sensibilité élevée de la rémunération des PDG à la performance (*Wealth-Performance-Sensitivity*, WPS) répondent à la menace de sortie. Cependant, même parmi les entreprises du quartile supérieur de la distribution de WPS, l'effet de sortie est de moindre ampleur que l'effet de voix. Je ne trouve pas de preuve que les entreprises avec un coût du capital élevé répondent davantage à la menace de sortie. Au contraire, les résultats, bien que faiblement significatifs, tendent à montrer que les entreprises avec un coût du capital plus faible sont les plus réactives.

Mon troisième résultat montre que les entreprises répondent davantage à la pression de voix lorsque les administrateurs du conseil cherchent à être réélus. Je tire ce résultat en exploitant les différences dans les structures des conseils d'administration et les variations exogènes dans les taux de renouvellement des conseils. La majorité des conseils d'administration américains sont entièrement réélus chaque année, mais certaines entreprises ont des administrateurs de conseil organisés en "classes" avec des mandats de trois ans se chevauchant. Je constate que cette structure de conseil échelonnée rend les entreprises beaucoup moins réactives à la pression de voix. Pour établir la causalité, j'exploite les changements d'une année à l'autre dans le taux de renouvellement du conseil découlant du fait que toutes les classes d'un conseil n'ont pas la même taille. L'effet de la voix sur les entreprises avec des conseils d'administration échelonnés se concentre dans les années où les classes plus importantes sont réélues.

Enfin, j'illustre le mécanisme de la voix à travers les réactions des entreprises à une campagne activistes réussie dans leur environnement proche. Plus précisément, j'utilise la révolte menée par des fonds activistes contre le président du conseil d'administration

de Seaworld comme un choc pour les entreprises du même secteur et avec une propriété de voix partagée. Cette campagne était motivée par des années de réputation dégradée en raison d'accusations de mauvais traitement des animaux et de rémunération excessive des dirigeants. En réponse, les entreprises du réseau de Seaworld ont significativement amélioré leur comportement de RSE dans les trimestres suivants.

En conclusion, cet article développe et applique un cadre portable pour identifier les préférences des fonds et leur influence sur les politiques des entreprises. Dans l'ensemble, mes résultats indiquent que les cadres et les administrateurs répondent à la demande de leurs actionnaires en faveur de la pro-socialité uniquement lorsqu'ils ont des incitations personnelles à le faire. Cette conclusion éclaire un mécanisme crucial conduisant les entreprises à maximiser le bien-être des actionnaires, plutôt que simplement les profits (Hart and Zingales, 2017).

Chapitre 2 | Le Coût Partagé de la Valeur des Actionnaires

Les désaccords entre actionnaires sont courants mais souvent méconnus. Alors que les actionnaires tentent d'influencer les gestionnaires, des politiques ont été mises en place pour informer les actionnaires (par exemple, Desai et al., 2007) et résoudre les conflits en leur permettant de faire des propositions et de voter lors des assemblées générales annuelles (AGA) (par exemple, DeMarzo, 1993, Bouton et al., 2022). Cependant, certains actionnaires peuvent également influencer les gestionnaires par des canaux privés, réduisant ainsi la capacité des actionnaires non connectés à accéder aux gestionnaires et limitant la connaissance managériale des préférences des actionnaires concernant les décisions des entreprises.

La responsabilité sociale ajoute une autre dimension aux conflits entre actionnaires car ceux-ci peuvent être en désaccord non seulement sur la rentabilité des actions des entreprises, mais aussi sur leurs implications sociales (Landier et al., 2009, Fioretti, 2022). Considérez la décision de Ford Motor de convertir certaines de ses installations de production automobile pour produire et faire don de ventilateurs médicaux aux hôpitaux pendant la pandémie lorsque les ventilateurs, essentiels pour le traitement des patients atteints de COVID-19, étaient en pénurie. En raison de ses coûts, les actionnaires peuvent avoir des avis différents sur la décision de l'entreprise. Ceux qui tirent une « valeur » du soulagement de la Covid peuvent l'avoir soutenu malgré de plus faibles rendements financiers car leurs dons en espèces ne pouvaient pas aider les hôpitaux à se procurer des ventilateurs (Hart and Zingales, 2017). Les actionnaires facilement associés à Ford Motor pourraient également bénéficier de la couverture médiatique de la générosité de l'entreprise, comme c'est le cas de Bill Ford, membre de la famille Ford qui,

lors d'une interview avec CBS, a approuvé le don de ventilateurs.[27] D'un autre côté, pour des actionnaires tels que les ménages américains qui ne bénéficient pas de retours privés similaires, les dons ressemblent à des impôts (Friedman, 1970). Ces différences de préférences soulèvent des questions sur les conséquences de la poursuite des valeurs de certains actionnaires au détriment des autres.

Notre principale contribution est d'étudier empiriquement les coûts partagés de l'influence des actionnaires en établissant un lien de causalité entre leurs préférences et les décisions prosociales des grandes entreprises mondiales. Pour surmonter le principal problème auquel nous sommes confrontés, à savoir que l'influence des actionnaires n'est pas observable, nous nous concentrons sur des contextes où une urgence soudaine place les entreprises dans une position avantageuse pour procurer à la société des biens et des services nécessaires par rapport à ce que les actionnaires peuvent réaliser par le biais de dons en espèces. Exploitant l'occurrence exogène des AGA en tant que choc sur la couverture médiatique des entreprises, nous constatons que les actionnaires les plus susceptibles de bénéficier de retours d'image des décisions prosociales de leur entreprise demandent des changements positifs. En revanche, les actionnaires ayant peu d'opportunités d'extraire des gains privés considèrent ces demandes comme des externalités et s'y opposent parce que les coûts associés peuvent réduire les bénéfices et les perspectives de croissance d'une entreprise. En conséquence, la capitalisation boursière et le revenu d'exploitation diminuent d'environ un à trois points de pourcentage de plus pour les entreprises les plus exposées à ces externalités, entraînant des résultats défavorables pour les actionnaires « silencieux » et « non entendus ». Ces pertes proviennent de dépenses inefficaces réduisant les fonds actuels qui auraient autrement été investis, décrivant un cercle vicieux limitant la productivité future.

Motivés par un modèle théorique stylisé d'un concours où les actionnaires ayant des préférences différentes concernant une action prosociale d'entreprise concourent pour influencer les gestionnaires (par exemple, Konrad et al., 2009), nous nous attendons à ce que, net des inclinations prosociales, les actionnaires détenant une part significative dans l'entreprise et ne tirant pas de gains privés de sa décision prosociale s'opposent à l'action si elle réduit les bénéfices de l'entreprise. Au contraire, les actionnaires qui peuvent tirer des gains privés de l'action prosociale la soutiendront si ces gains dépassent leurs pertes. Également inspirés par la littérature sur la propriété commune (par exemple, Azar et al., 2018, Backus et al.,

[27]" [...] When we look at this crisis– as a country and said, you know, which industry is positioned to help us not only in terms of sophisticated machinery, but can do a lotta them and a lotta them quickly, the auto industry is uniquely positioned to do that" (O'Donnell, 2020). Cet exemple est illustratif car la production de ventilateurs a été soutenue économiquement par le Defense Production Act (c'est-à-dire des contrats gouvernementaux), tandis que cet article se concentre uniquement sur les dons volontaires.

2021), nous identifions les actionnaires précédents dans les investisseurs institutionnels – des intermédiaires financiers tels que les fonds communs de placement et les banques – que le public associe difficilement à une entreprise spécifique car ils possèdent des actions dans de nombreuses entreprises, et les actionnaires ultérieurs dans les actionnaires individuels et familiaux, qui sont synonymes d'une entreprise.[28] Il est important de noter que certains de ces actionnaires peuvent être des managers passés ou actuels sans affecter nos résultats, comme discuté ci-dessous.

Notre cadre empirique repose sur une urgence soudaine où le public demande aux entreprises de prendre des mesures prosociales coûteuses et sur la variation exogène du calendrier des AGA entre les entreprises, ce qui, comme nous le montrons, augmente la couverture médiatique d'une entreprise, augmentant ainsi l'attention médiatique de ses actionnaires les plus reconnaissables. L'International Shareholder Services (ISS), un leader mondial des services de vote par procuration, exige que les entreprises permettent 90 jours entre la date à laquelle les actionnaires reçoivent les documents sur les propositions de l'AGA et l'AGA. Considérez la pandémie récente comme une urgence similaire. Le premier cas de Covid signalé aux États-Unis est survenu le 15 janvier 2020 (Holshue et al., 2020) : comme les entreprises avec des AGA prévues pour les 90 jours suivants ne pouvaient pas déplacer leurs dates légalement (SEA, 1934), l'attention médiatique accrue due à la période de l'AGA est indépendante des préférences des actionnaires et des gestionnaires concernant les dons, la composition du corps des actionnaires et leur accès aux gestionnaires, et le statut financier et opérationnel d'une entreprise. Ces caractéristiques rendent notre approche portable à travers les crises (ou même les pays) et les époques.

Par conséquent, nous estimons l'impact des préférences des actionnaires sur les décisions des entreprises comme la différence dans les taux de dons observés d'ici le 15 avril 2020, dans quatre groupes d'entreprises : *i)* la différence entre les entreprises traitées (c'est-à-dire avec une AGA avant 90 jours depuis le début de la crise) avec et sans grands actionnaires individuels (ou institutionnels) et *ii)* la même différence entre les entreprises témoins (c'est-à-dire sans projets d'AGA dans cette période). Comme les entreprises ont fait des dons en espèces et en biens comme des masques faciaux, des gels désinfectants et des logiciels, nous nous concentrons sur l'explication du pourquoi des entreprises ont fait des dons plutôt que sur la valeur des dons. Chez les entreprises du S&P 500, les dons en espèces représentaient en moyenne 1% du BAIIA seul, un coût substantiel pour les actionnaires de l'entreprise mais une grande publicité pour

[28]Nous présentons des vérifications de robustesse en utilisant des mesures d'association plus sophistiquées entre une entreprise et ses actionnaires, en tirant parti des données de recherche Google pour les entreprises et les actionnaires.

les plus visibles.

Nous constatons qu'à partir du 15 avril, les entreprises du S&P 500 traitées sont 9% plus susceptibles de faire un don pour le soulagement de la Covid si leur corps actionnarial inclut de grands actionnaires individuels avant la pandémie par rapport à l'entreprise moyenne du S&P 500. En revanche, les entreprises traitées avec de grands actionnaires institutionnels sont 15% moins susceptibles de faire un don par rapport à l'entreprise moyenne du S&P 500. La demande des consommateurs pour les dons liés à la Covid, la volonté managériale, la pression des pairs provenant des concurrents donateurs et les retours financiers n'expliquent pas nos résultats.

Nous validons le mécanisme de gain d'image en montrant un écart instantané et soutenu dans les recherches Google des noms des actionnaires individuels d'une entreprise par rapport à ceux de ses actionnaires institutionnels autour de la date des nouvelles des dons ; cet écart s'élargit d'environ 40% dans chacun des dix jours suivant un don. Néanmoins, les actionnaires institutionnels ne sont pas nécessairement contre les dons liés à la Covid : plusieurs entreprises financières du S&P 500 ont fait des dons directement, mais leurs dons sont négativement corrélés avec ceux des entreprises du S&P 500 dans leurs portefeuilles. Ainsi, les actionnaires soutiennent les dons seulement si leur influence génère des avantages privés directs, créant une externalité sur les autres actionnaires. Ces retours peuvent être fondés microéconomiquement comme des utilités de *warm glow* (par exemple, Andreoni, 1989) ou des gains de réputation par le biais du signalement de vertu (par exemple, Bar-Isaac et al., 2008).

Nous démontrons la portabilité de notre cadre de travail de deux manières. Premièrement, nous étudions un autre événement focal de la dernière décennie, à savoir la décision des multinationales américaines de renoncer à leurs investissements russes ou d'interrompre leurs relations avec leurs fournisseurs russes au début de l'invasion ukrainienne en 2022. À cet égard, nous ne prétendons pas que quitter la Russie était le choix le plus bénéfique pour le bien-être, mais plutôt que les sorties précoces pourraient, d'une part, recevoir une plus grande attention médiatique et, d'autre part, être particulièrement coûteuses pour les actionnaires si elles n'étaient pas correctement planifiées. Nos résultats concernant les directions de l'influence sont cohérents, avec de grands actionnaires institutionnels s'opposant aux décisions de sortie et les actionnaires individuels soutenant la rupture des liens avec la Russie. Deuxièmement, nous élargissons le champ de notre mécanisme d'influence en enquêtant sur la couverture médiatique ESG des entreprises et les dons au cours de la dernière décennie. Conformément à nos résultats précédents, une grande détention d'actions individuelles est associée à moins d'incidents prosociaux et plus de dons dans le mois de l'AGA, validant notre utilisation des AGA pour l'identification.

En fournissant des biens indisponibles sur les marchés, comme des gels désinfectants aux hôpitaux ou en exerçant une pression sur un État vilain en interrompant les relations commerciales, les entreprises avaient un avantage sur les actionnaires pour créer une valeur sociale. Comme les grands actionnaires individuels bénéficiaient des réponses de ces entreprises, la poursuite de leurs valeurs impliquait des coûts élevés pour les autres. En utilisant le revenu d'exploitation et la capitalisation boursière comme mesures de ces coûts, nous constatons que ces variables ont diminué d'environ un à trois points de pourcentage de plus pour les entreprises les plus exposées à ces externalités. Dans les deux cas, ces baisses sont dues à une augmentation des coûts d'exploitation, car les revenus sont restés constants entre les entreprises traitées et témoins. En effet, dans le cas de la Covid, nous constatons que l'investissement a diminué d'environ 6% en 2020 et 2021 chez les entreprises les plus exposées, entraînant une productivité réduite qui s'est accumulée au fil du temps, coûtant aux actionnaires environ 3% du bénéfice par action (BPA) moyen dans la période antérieure.[29] D'autre part, l'influence des actionnaires sur la crise russo-ukrainienne a conduit les entreprises traitées à quitter précipitamment la Russie, avec les entreprises les plus exposées renonçant à 20% de plus d'investissements que les entreprises témoins. Par conséquent, les actionnaires non entendus ont souffert : les coûts de restructuration en 2022 ont érodé 5% du BPA des entreprises les plus exposées. En conclusion, la poursuite des valeurs de quelques actionnaires coûte cher aux autres, aujourd'hui comme demain (par exemple, Bartlett and Bubb, 2023, Edmans, 2023).

Chapitre 3 | *La Promesse de l'Aube:* Fragmentation du Marché et Liquidité lorsque les Dark Pools sont Suspendus

Des changements technologiques et réglementaires récents ont révolutionné la manière dont les actions sont échangées. Alors que les bourses nationales agissaient autrefois comme des quasi-monopolistes, le trading d'une action se déroule désormais sur plusieurs plateformes simultanément. Le développement de lieux de négociation alternatifs et auto-régulés a entraîné une baisse des frais et une augmentation de la vitesse de trading (Pagnotta and Philippon, 2018), mais a également soulevé des préoccupations quant à leur impact sur la liquidité. Parmi eux, les dark pools ont attiré une attention particulière de la part des régulateurs et des universitaires. En cachant leur carnet d'ordres et en offrant une amélioration potentielle des prix, ils sont

[29]La perte de BPA en 2020-21 représente plus de 8% par écart type de la part d'une entreprise dans ses actionnaires individuels parmi ses actionnaires détenant au moins 5% de participation (ATE). Parmi les entreprises avec de grands actionnaires individuels, une AGA au début de la pandémie a diminué le BPA de 21% (ATT), ce qui suggère des coûts considérables pour les actionnaires non entendus.

plus susceptibles d'attirer des investisseurs non informés, augmentant ainsi la part des traders informés sur la bourse de référence, ce qui nuit à la liquidité (Glosten and Milgrom, 1985, Zhu, 2014). Cependant, estimer l'impact des dark pools sur la liquidité des bourses d'actions rencontre au moins deux défis : *i)* il n'y a aucune garantie que les ordres envoyés aux dark pools auraient été envoyés aux lieux d'échange transparents - et non à d'autres types de lieux de négociation - dans un monde sans dark pools, et *ii)* il existe une relation endogène entre la liquidité et la sélection du lieu de négociation.

En utilisant la réglementation européenne MiFID II comme un quasi-expérience naturelle, cet article étudie l'effet de l'interdiction des dark pools sur la fragmentation du marché et la liquidité. Mise en œuvre en 2018, MiFID II introduit un plafond sur l'utilisation des dark pools dans l'Union européenne. Sur une période de douze mois glissants, le trading de toute action sur les dark pools est limité à 8% de son volume. Un dépassement de ce seuil signifie que le trading dark pour cette action est suspendu pendant six mois. Plus de 700 actions ont été soumises à cette suspension le 12 mars 2018, et l'impact a été significatif : les dark pools européens ont perdu un tiers de leur part de marché, presque du jour au lendemain. Je développe un modèle simple basé sur Zhu (2014) qui prédit qu'une telle réglementation devrait améliorer considérablement la liquidité sur les bourses d'actions.

Premièrement, j'estime qu'entre un tiers et la moitié des volumes dark sont redirigés vers les bourses de référence transparentes lorsque l'accès aux dark pools est suspendu. Les volumes dark restants sont principalement redirigés vers des enchères périodiques, tandis que l'impact sur les Internalisateurs Systématiques, le trading de gré à gré et les lieux de négociation transparents alternatifs est insignifiant. En supposant que les traders trient les différents types de lieux de négociation en fonction de leur coût et de leur immédiateté, une analyse de "hiérarchie de choix" (Menkveld et al., 2017) révèle que les dark pools se situent entre les lieux transparents et les enchères. Ils attirent relativement plus de traders patients que les premiers, et relativement plus de traders impatients que les derniers. L'interdiction des dark pools introduit un compromis direct entre les lieux transparents et les enchères, expliquant pourquoi ce sont les deux types de lieux qui gagnent des parts de marché après l'interdiction.

Deuxièmement, en utilisant la réglementation pour surmonter la relation endogène entre la liquidité et la sélection du lieu de négociation, cet article identifie l'effet causal de l'interdiction sur la liquidité. Pour garantir la comparabilité entre les actions traitées et les actions témoins, j'implémente d'abord une procédure d'appariement par score de propension, basée sur les covariables de base pré-traitement, et j'exécute une régression à deux effets fixes sur l'échantillon apparié. Ensuite, j'implémente une approche de différence-en-différences synthétique (Arkhangelsky et al., 2021), avec des pondérations unitaires et temporelles, basée

sur les mesures de liquidité pré-traitement. Mes résultats montrent que la suspension des actions du trading dans le noir réduit leur spread de 10% et l'impact sur les prix de 5%.

Enfin, je documente que l'effet est concentré parmi les actions avec un niveau élevé de détention par les investisseurs particuliers, un proxy courant pour le trading non-informé (Foucault et al., 2011, Peress and Schmidt, 2019). Un niveau plus élevé de détention par les investisseurs particuliers est associé à une plus grande diminution du spread et de l'impact sur les prix, mais il n'est pas associé à une augmentation plus forte de la part de marché de la bourse de référence transparente. Ce dernier résultat confirme que c'est le degré d'informativité des ordres, et pas seulement les volumes de trading, qui cause l'amélioration de la liquidité.

Dans l'ensemble, ces résultats vont dans le sens de la prédiction théorique selon laquelle les dark pools attirent des ordres non informés qui seraient autrement envoyés vers des lieux transparents (Zhu, 2014). Ils tendent à confirmer que les dark pools sont préjudiciables à la qualité du marché en augmentant le risque de sélection adverse sur les bourses d'actions. En résumé, l'interdiction des dark pools redirige (une partie) des volumes de trading vers les bourses transparentes de référence, réduisant la part de trading informé et améliorant la liquidité.

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