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# The effects of mutual fund decarbonization on stock prices and carbon emissions[☆]

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ABSTRACT

This study seeks to determine whether mutual fund decarbonization affects the stock prices of divested firms and contributes to the reduction of these firms' carbon emissions. Using a new methodology to identify equity mutual funds' decarbonization trades, we calculate a metric of *decarbonization selling pressure* (DSP) on stocks. Controlling for endogeneity and selection bias, we find that high DSP sustainably pressures stock prices downwards. Furthermore, we find that divested firms experiencing a stock price decline subsequently reduce their carbon emissions compared to non-divested firms. This finding is consistent with theoretical predictions. Various tested alternative explanations, such as shareholder intervention and financial selling pressure, cannot diminish these results. Overall, our findings support the divestment movement's hope that a critical mass of investors is able to reduce carbon emissions.

*Short presentation:* English version: https://youtu.be/dorMMn2BBn4, German version: https://youtu.be/i3r30iRbtI8.

## 1. Introduction

In the global war against climate change, an important role has been assigned to the financial system to redirect capital flows away from climate-damaging economic activities and toward climate-friendly economic activities (European Commission, 2018). These goals can be achieved by divesting from carbon-intensive firms and investing in low-carbon firms instead. The divestment from carbon-intensive firms to reduce a portfolio's carbon intensity is often referred to as "portfolio decarbonization" (Portfolio Decarbonization Coalition, PDC, 2017). Investor initiatives such as the PDC aim to mobilize a critical mass of investors to decarbonize their portfolios to encourage carbon-intensive firms to decrease their carbon emissions (CE) and accelerate the transition to a low-carbon economy (PDC, 2017). As the main impact channel predicted by theory, divestment from carbon-intensive firms is expected to increase their cost of capital and in turn their stock price and thus put pressure on these firms to reform—that is, to decrease their CE (e.g., Heinkel et al. (2001)). Moreover, publicly divesting is expected to increase stakeholders' awareness of a firm's climate-damaging behavior, which diminishes future cash flows and increases reputational risk, thereby putting further pressure on stock prices (e.g., Ansar and Caldecott (2013); Dordi and Weber (2019)). Whether divesting from carbon-intensive stocks truly has this intended effect is currently an open question.[1] We fill this gap by providing one of the first empirical analyses of the effect of real

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[1] Haas and Popov (2021) show that stock markets are generally able to drive carbon emissions reductions in carbon-intensive industries. Furthermore, several studies theoretically discuss the pro and contra arguments of divesting from fossil-fuels. For example, Dawkins (2018); Braungardt, van den Bergh and Dunlop (2019); Bergman (2018); Richardson (2017); Ayling (2017); Ritchie and Dowlatabadi (2015).

portfolio decarbonization in a large sample of US and European equity mutual funds on the stock prices and CE of global firms.

While the effectiveness of divestment is still in question, its growing popularity among private and institutional investors is not. Many investors have publicly committed to selling their shares of companies operating in the fossil fuel industry ("fossil fuel divestment", Gofossilfree (2019)). As of 2021, over 1,300 institutions (e.g., pension funds, investment funds and university endowments) representing approximately US$ 14.5 trillion and more than 58,000 individuals representing approximately US$ 5.2 billion in assets, have publicly pledged to reduce their investments in the fossil fuel industry.[2] [3] Therefore, it is important to answer the question of whether this global divestment effort has any significant and sustainable impact on stock prices and on the CE of divested firms. We find robust evidence that it does, as divested firms experience a strong and sustainable stock price decrease, on average. Furthermore, we show that divested firms experiencing a stock price decline subsequently reduce their CE on average compared to non-divested firms, which on average increase their CE. These findings are consistent with the equilibrium predictions of Heinkel et al. (2001).

Our analysis is based on a large dataset of US and European equity mutual fund holdings combined with comprehensive information regarding the individual holdings' CE. Mutual funds manage a large proportion of investors' capital, which provides them with leverage on stock prices (e.g., Coval and Stafford (2007)). Furthermore, many investment companies have recently committed to decarbonizing their portfolios, which may provide the critical mass necessary to put enough pressure on stock prices for divestment to be effective. Mutual fund decarbonization thus provides an ideal laboratory for investigating the effects of divestment on stock prices and the CE of divested firms.

In the first step of our investigation, we calculate the "weighted average carbon intensity" (WACI) for each mutual fund, the key metric for funds' carbon intensity (CI) recommended by the Task Force on Climate-Related Financial Disclosures (TCFD) to compare equity portfolios.[4] Using the WACI, we analyze mutual funds' hypothetical portfolio decarbonization potential. We find that by selling only 1.5%—that is, the single dirtiest holding—funds could reduce their WACI by 24.1% on average. Likewise, selling only 7.8% of the portfolio—that is, the top five dirtiest holdings—would cut the WACI by more than half (−57.8%) on average.

In the second step, we implement a novel approach to identify actual mutual fund decarbonization and to measure the resulting pressure on stock prices. Therefore, we modify and extend a widely cited method used by Coval and Stafford (2007) and Khan et al. (2012) to specifically distinguish decarbonization trades from other trades. In essence, we calculate funds' active quarterly WACI change and identify the bottom 10% with the highest reduction as "decarbonizing funds." Then, we look at the trades of these fund-quarters and isolate "decarbonization trades". We use a conservative approach to ensure that we capture intentional decarbonization. In each quarter, all decarbonization trades are aggregated to arrive at our novel metric of funds' "decarbonization selling pressure" (DSP) on stocks.

In the third step, we test whether high DSP is associated with a significant and sustainable decline in stock prices using event studies. To ensure that the results are not artifacts from endogeneity or selection bias, we follow two approaches: 1) We contrast our main treatment sample of high DSP stocks (HDSP) with an alternative treatment sample of stocks with concurrent high "general selling pressure" (HGSP) originating from carbon-unrelated sources. We find that HDSP stocks suffer a cumulative industry-adjusted return of −6.7% over 24 months when divested, compared to an immediate decline of only −1.4% for HGSP stocks. The difference between the samples is statistically significant, while both are significantly different from an untreated control sample of stocks with no concurrent selling pressure (NSP). 2) Within the sample of stocks with high carbon intensity (HCI), we contrast our divested treatment sample with an untreated control sample of non-divested stocks to account for a general price trend among HCI firms. While divested HCI stocks suffer a cumulative industry-adjusted return of −7.3% over 24 months when divested, non-divested HCI stocks report only a small and steady abnormal decline of −1.2% over the same period. The difference between the treatment and control samples was also statistically significant. Both comparisons showed that the strong price decline following divestment is neither an effect of other sources of price pressure nor a general trend among HCI firms. These event study findings are confirmed by alternative calendar time panel regressions and are robust to various alternative explanations, specifications, and methods.

In the final step of our main investigation, we venture to test the effects of portfolio decarbonization on the CE of divested firms. Therefore, we contrast cumulative changes in CE of the HDSP sample against those of the various control samples. As a general trend, the HGSP and NSP samples show a steady increase in CE of +6.4% and +8.0%, respectively, over the 48 months after the respective event. In contrast, divested HDSP stocks decrease their CE by −2.3%. Among HCI stocks, divested HCI stocks decrease their CE by −2.8%, compared to an increase of +1.4% for non-divested HCI stocks. This means that HCI stocks increased their CE less compared to the general trend in our sample, probably due to changes in climate-related legislation or changes in energy and emission prices. However, our results clearly show an additional effect of portfolio decarbonization on the CE of divested firms. These event study findings are also confirmed by alternative calendar time panel regressions and are robust to various alternative explanations, specifications, and methods.

## 2. Literature review and theoretical foundation

The question of whether environmental considerations affect mutual fund and investor behavior in general is at the heart of a growing body of literature on the sustainability of mutual funds. For instance, Riedl and Smeets (2017) show that investors value sustainable mutual funds despite lower returns and higher management fees because these funds align with their personal social attitude. Hartzmark and Sussman (2019) show that the introduction of the Morningstar sustainability rating in 2016 presented a shock to the US mutual fund market, as funds categorized as unsustainable suffered significant outflows. Ammann et al. (2019) find similar results but show that institutional investors react less strongly. Ceccarelli et al. (2020) show similar results for the introduction of Morningstar's low carbon designation. Thus, mutual funds are under pressure from investors to become more sustainable and to reduce their WACI.

Accordingly, Bolton and Kacperczyk, 2021 observe significant decarbonization efforts by mutual funds, especially in the US and in Europe. Boermans and Galema (2019) show that Dutch pension funds have been actively decarbonizing their portfolios. Using institutional ownership data, Benz et al. (2020) find evi-

[2] https://gofossilfree.org/divestment/commitments/

[3] In addition, asset owners and asset managers with a combined value of over US$ 100 trillion AUM committed to investing responsibly and to incorporating environmental issues in their decision-making (PRI (2020)). Moreover, investors representing US $52 trillion of AUM signed the investor initiative ClimateAction100+, which focuses on the 160 largest GHG emitters (Climate Action 100+, 2020).

[4] Throughout this paper, we use several abbreviations, especially for the large number of control groups for our treatment group of divested companies. We have collected these abbreviations for the readers' convenience in the Appendix.

dence that institutional investors engage in decarbonization herding. Alok et al. (2020) provide evidence that fund managers overreact to climatic disasters. However, none of these studies looks at the effects of mutual fund decarbonization on stock prices and CE.

As one of the few studies looking at the effect of divestment on stock prices, Dordi and Weber (2019) analyze divestment announcements involving the top 200 global oil, gas, and coal companies. In addition to short-term effects, divestment announcements might lead to a shift in investor perception and negative abnormal returns in the long run. They conclude that divestment actions can influence the share price of the target companies, challenging the efficient market hypothesis. However, they look at announcements and not at actual divestment and only analyze a small and very specific selection of firms. Furthermore, they do not analyze the effects of divestment announcements on CE.

While there is little empirical work on the actual effectiveness of divestment, several studies theoretically address the question of whether differing investor preferences can have an impact on firms' environmental behavior. One of the pioneering works comes from Heinkel et al. (2001), who present an equilibrium framework to characterize the relation between 1) the market share of green investors for whom polluting firms are unacceptable, 2) the share prices and costs of capital of polluting firms, and 3) polluting firms' decisions to reform at specific reforming costs to become acceptable for green investors. Following Heinkel et al. (2001), an increasing market share of green investors—that is, more investors boycotting or divesting from polluting firms—reduces the potential investor base of polluting firms and leads to a concentration of their shares in the portfolios of preference-neutral investors. This reduces preference-neutral investors' risk sharing opportunities and forces them to deviate from the market portfolio, leading to higher return expectations. These theoretical considerations are supported by Fama and French (2007), who show that preference-neutral investors require a premium for balancing out the portfolio choices of investors with a particular non-financial preference (see also Merton (1987)). Consequently, divested polluting firms face a higher cost of capital and lower share price (Hong and Kacperczyk (2009)). Finally, managers of boycotted or divested polluting firms may be threatened with reduced compensation, which is often directly linked to share price performance (Edmans et al. (2017)).[5]

All these aspects create incentives for the management of divested firms to reform—that is, to reduce CE—to become acceptable for green investors. This would increase their investor base, improve risk sharing opportunities among investors, lower their cost of capital, and increase share prices. However, reforming the firm is costly. According to Heinkel et al. (2001), a polluting firm decides to reform if the cost of reforming is lower than the increase in its cost of capital. Thus, the greater the divestment pressure—that is, our new measure DSP—the higher the increase in cost of capital, the higher the probability that the cost of reforming is below the increase in cost of capital so that the firm ultimately decides to reduce CE to become acceptable for green investors.

In support of this theoretical foundation, Angelis et al. (2020) show that investors are able to influence companies to decrease CE by raising their cost of capital. Gollier and Pouget (2014) argue that by collectively divesting from firms with high pollution, investors can create incentives to transform if doing so will attract more investors. More specifically, they show that 8% of investors applying the same screening approach is sufficient to incentivize companies to invest in the carbon-efficient technologies required to mitigate climate change. Pástor et al. (2020) build on the model created by Heinkel et al. (2001) and confirm that sustainable investors generate social impact without direct engagement by shareholders.

## 3. Data and sample construction

### 3.1. Stock-level carbon emissions

We obtained data on annual stock-level CE from three major carbon data providers for the period from 2010 to 2017: Refinitiv Datastream, CDP, and Sustainalytics. We followed the recommendations of the TCFD and standardized CE by year-end net sales to gain comparability between companies (TCFD, 2017). The "stock-level carbon intensity" (CI, in metric tons/\$) indicates how many metric tons of carbon dioxide equivalents (scope 1 + 2)[6] are emitted for one dollar of net sales for each firm $i$ in each year $t$ and reflects the efficiency of turning CE into net sales. Another reason for using this metric is that divestment policies are concentrated on CI rather than CE (Bolton and Kacperczyk, 2021). We apply standard filters to cleanse the carbon data and combine all three carbon datasets into one CI superset. We impute missing data to prevent our results from being affected by data availability.[7]

$$CI_{i,t} = \frac{Scope\_1\&2\_CE_{i,t}}{Year\_end\_net\_sales_{i,t}} \quad (1)$$

The superset covers the CI of 9,954 companies representing approximately \$69 trillion of market capitalization worldwide in 2017, which equals 87.1% of the global stock market.[8] The companies in our sample emit 1.9 million metric tons of $CO_2$ equivalents on average (scope 1 + 2). The mean stock-level CI is 0.0004 tons of CE per dollar net sales. Both statistics are highly right-skewed, indicating that a small proportion of companies are responsible for a huge proportion of the sample's aggregate CE. In general, these statistics regarding CE are similar to other studies (e.g., Bolton and Kacperczyk, 2021). In addition, we obtain the monthly total return index and other stock characteristics from Refinitiv Datastream and follow Ince and Porter (2006) to cleanse the data of known contaminations. Summary statistics for the superset are presented in Table A1 (CE availability) and Table A2 (stock characteristics) of the Internet Appendix.

### 3.2. Mutual fund holdings

To calculate funds' WACI, we match the stock-level CI information to mutual fund holdings. Mutual fund holdings are obtained from Morningstar.[9] Our raw holdings dataset includes the quarterly holdings reports of 11,650 actively managed US and European equity funds over the period from 1983 to 2017. To ensure high data quality, we apply several standard filters. We only include mutual funds in our analysis with a CI coverage of at least 60% of the funds' equity assets under management (AUM). Table A3 of the Internet Appendix illustrates the funds' holdings' CI data coverage.

[5] Zerbib (2020) argues that divested stocks are subject to a taste premium and two exclusion premiums arising from the reduction in the investor base. Luo and Balvers (2017) show the existence of a boycott risk factor which compensates for the extra risk of holding boycotted stocks in excess of otherwise efficient market weights.

[6] Scope 1 emissions reflect firms' direct emissions. Scope 2 accounts for emissions from the generation of purchased electricity consumed by the firm (WBCSD; WRI 2015).

[7] The superset is an unbalanced panel because, e.g., some companies start reporting later than others. Therefore, we impute missing data using extrapolation or industry medians to achieve a balanced sample. This resembles the estimation approach of the data providers. Overall, 39 percent of the annual CE observations are reported by the companies, 55 percent are estimated by the data providers, and our own imputation applies to the remaining six percent. On average, our imputed CE are very small so that this should not compromise our analysis (for details see Kalesnik, Wilkens and Zink (2020)).

[8] https://data.worldbank.org/indicator/CM.MKT.LCAP.CD.

[9] For details on the Morningstar holdings data, see, e.g., Elton et al. (2012).

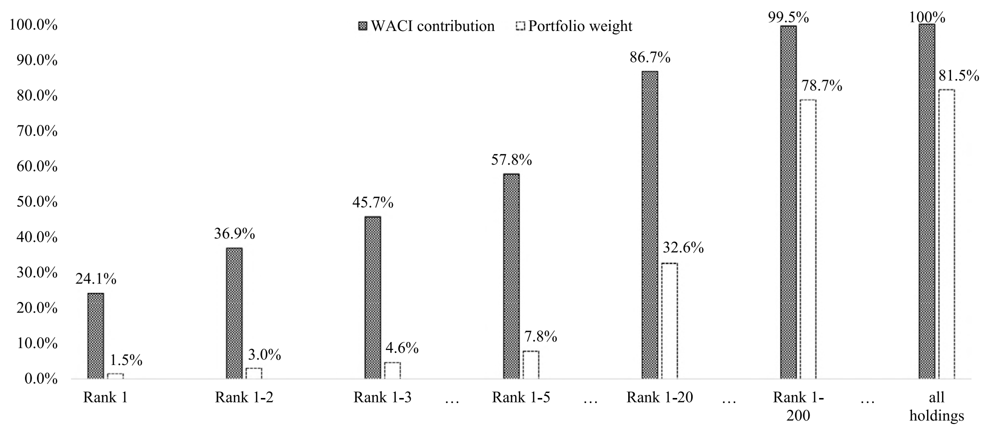



**Fig. 1.** Hypothetical decarbonization potential.
This figure compares the average WACI contribution with the corresponding average portfolio weight each quarter for each fund for the survey period from Q1/2010 to Q3/2017. The calculation of *WACI contribution* is described in Section 4.2. Rank 1 is the holding with the highest WACI contribution in the respective fund portfolio. For instance, Rank 1–2 aggregates the average WACI contribution for the holdings with the highest and second-highest WACI contribution. *Portfolio weight* represents the average portfolio weights reported by Morningstar.

The final dataset contains 4,646 actively managed US and European open-end equity mutual funds in the period from Q1/2010 to Q3/2017. This dataset comprises more than \$5.7 trillion AUM in 2017, which equals 14.3% of the size of the combined US and European stock markets.[10] Other fund-level characteristics (e.g., expense ratio, turnover ratio) are obtained from Morningstar Direct. Table A4 of the Internet Appendix presents summary statistics of the mutual fund sample.

## 4. Mutual fund carbon intensity and decarbonization

### *4.1. Fund-level carbon intensity*

The TCFD recommends that asset managers disclose the "weighted average carbon intensity" (WACI, in tons/\$) for each individual mutual fund. It measures the fund's exposure to carbon-intensive companies and enables comparisons between investment portfolios (TCFD, 2017). The WACI is widely used, e.g., to construct low-carbon indices, and many investors voluntarily disclose this metric (TCFD, 2020). We calculate the WACI for each fund $j$ in each quarter $t$ using the CI of each stock $i$. For the holdings not covered by our stock-level CI superset, we assume a CI of zero. In total, we calculate the WACI for 107,910 fund-quarter observations. Table A5 of the Internet Appendix presents summary statistics of the WACI for different investment styles and different sector designations.

$$WACI_{j,t} = \sum_{i=1}^{n} Weighted\_CI_{j,i,t} = \sum_{i=1}^{n} Portfolio\_weight_{j,i,t} CI_{i,t} \tag{2}$$

### *4.2. Mutual funds' hypothetical decarbonization potential*

To analyze how easy it would be for funds to reduce their WACI by selling carbon-intensive holdings, we examined the extent to which each holding $i$ contributes to the fund's WACI in each quarter $t$. If the "WACI contribution" of a holding was 100%, the fund's WACI would be fully eliminated by divesting this holding.

$$WACI\_contribution_{j,i,t} = \frac{Portfolio\_weight_{j,i,t} CI_{i,t}}{WACI_{j,t}} \tag{3}$$

Fig. 1 ranks the holdings in each fund portfolio in descending order according to their WACI contribution and compares each holding's ranking to its portfolio weight. The results indicate that few holdings within a fund portfolio strongly determine its WACI. On average, the holding with the highest WACI contribution—that is, the single dirtiest holding—accounts for 24.1% of the WACI but reports a portfolio weight of only 1.5%. The five dirtiest holdings account for more than half (57.8%) of the funds' WACI but represent only 7.8% of the portfolio weight. This suggests that if fund managers decided to decarbonize, they would focus on very few holdings.

### *4.3. Actual mutual fund decarbonization*

In the following, we quantify actual decarbonization intended by mutual funds to attract new investors or to prevent incumbent investors from selling their shares. Therefore, we use the widely cited method of Coval and Stafford (2007) and Khan et al. (2012), who analyze the price impact of mutual fund fire selling. We modify the method to specifically identify decarbonization trades. Our procedure starts by noting whether a fund decarbonizes from one quarter to the next by calculating WACI changes following Eq. (4).

$$WACI\_change_{j,t,t-1} = \frac{\sum_{i=1}^{n} Weighted\_CI\_change_{j,i,t,t-1}}{WACI_{j,t-1}} \tag{4}$$

Since decarbonization is a discretionary decision to underweight individual carbon-intensive stocks, we distinguish between passive and active WACI changes. We define "passive WACI change" in Eq. (5) as the change that arises solely due to shifts in stock-level CI over which fund managers have little influence. "Active WACI change" in Eq. (6) consequently reflects shifts in portfolio weights. Going forward, we focus on active WACI changes and refer to negative changes as "active decarbonization" and to positive changes as "active carbonization."

$$Passive\_WACI\_change_{j,t,t-1} = \frac{\sum_{i=1}^{n} portfolio\_weight_{j,i,t-1} \Delta CI_{i,t,t-1}}{WACI_{j,t-1}} \tag{5}$$

$$Active\_WACI\_change_{j,t,t-1} = \frac{\sum_{i=1}^{n} \Delta\ portfolio\_weight_{j,i,t,1} CI_{i,t}}{WACI_{j,t-1}} \tag{6}$$

To identify funds that heavily decarbonized from one quarter to the next, we sort funds into deciles of active WACI change and identify funds in the bottom decile as actively "decarbonizing funds".

[10] https://data.worldbank.org/indicator/CM.MKT.LCAP.CD.

**Table 1**
Panel probit regression of heavy mutual fund decarbonization.

| | Coefficient | T-Statistic |
|---|---|---|
| WACI | 319.133*** | 4.22 |
| Turnover ratio | 0.155*** | 9.45 |
| AUM | −0.000*** | −5.27 |
| Net fund flow | 0.000 | 0.27 |
| Past performance | −0.004** | −2.11 |
| Hypothetical decarbonization potential | 0.003*** | 4.48 |
| Previously classified as decarbonizing fund | 0.156*** | 7.34 |
| PDC member | 0.082* | 1.94 |
| *Domicile Fixed Effects* | | |
| Europe | Base group | |
| United States | −0.065*** | −3.13 |
| *Fund Style Fixed Effects* | | |
| Large Growth | 0.253*** | 6.90 |
| Large Blend | 0.162*** | 4.39 |
| Large Value | 0.067* | 1.73 |
| Mid Growth | 0.193*** | 4.74 |
| Mid Blend | Base group | |
| Mid Value | 0.072 | 1.42 |
| Small Growth | 0.268*** | 5.96 |
| Small Blend | 0.060 | 1.21 |
| Small Value | 0.103* | 1.83 |
| Constant | −1.644*** | −40.14 |
| Observations | 79,887 | |
| Pseudo R-squared | 2.6% | |

This table presents probit panel regression results on a dummy variable indicating if a fund is identified as actively decarbonizing–that is, in the top 10% of active WACI reduction in a given quarter for the survey period from Q1/2010 to Q3/2017. *WACI* represents a fund's weighted average carbon intensity. *Turnover ratio* is an annual measure of funds' trading activity. *AUM* represents a fund's total assets under management, net of fees and expenses. *Net fund flow* is the net of all cash inflows and outflows of the fund on a quarterly basis. *Past performance* reflects the Sharpe ratio over the past 12 months. *Hypothetical decarbonization potential* is calculated by dividing the WACI contribution by the aggregate portfolio weight of the five dirtiest holdings of the previous quarter. *Previously classified as decarbonizing fund* is a dummy and indicates if the fund was identified as a decarbonizing fund in the previous quarter. *PDC member* is a dummy variable indicating if the fund's investment company has signed to the Portfolio Decarbonization Coalition. *Domicile* reflects the region in which the fund is domiciled. *Fund style* represents the Morningstar 3×3 equity style box.
Standard errors are clustered by fund.

### *4.4. Decarbonization in the cross-section of mutual funds*

To explore mutual fund decarbonization in more detail, we ran a panel probit regression to explain whether a fund was an actively decarbonizing fund (1) or not (0) with various fund characteristics. We controlled for domicile and style-fixed effects by including respective dummies. Standard errors are clustered by fund.

The results are presented in Table 1 and reveal that mutual funds with high WACI show a higher probability of decarbonizing, e.g., due to their poor performance in climate ratings (e.g., Ceccarelli et al. (2020)) or their increased awareness of carbon-related risk (e.g., Görgen et al. (2020)). Furthermore, the more active mutual funds are, the more likely they are to strongly decarbonize, as indicated by the positive coefficient of the turnover ratio. In contrast, fund size (AUM) is negatively related to the probability of strong decarbonization. Larger funds with larger holding positions may stretch decarbonization trades over several quarters to avoid negative price impacts. Thus, they only gradually reduce their WACI. There is no significant relation between fund flows and the probability of strong decarbonization. This creates further confidence in our method of identifying intentional decarbonization rather than flow-driven trades such as fire sales (Coval and Stafford (2007)). Past performance, as indicated by the Sharpe ratio, is negatively related to the probability of strong decarbonization, albeit only thinly significant. A possible explanation may be that funds try to compensate for poor financial performance with a stronger environmental performance to be competitive for money inflows (e.g., Ceccarelli et al. (2020)).

As expected, past hypothetical decarbonization potential is positively linked to decarbonization probability. Moreover, decarbonization seems to be persistent over time, as indicated by the lagged dependent variable. Being a signatory to the PDC is slightly and positively related to the probability of strong decarbonization. Even though we would have expected a stronger relationship, some PDC signatories are "walking the talk" and decarbonizing their portfolios to a higher extent than non-signatories (e.g., Humphrey and Li (2021); Gibson et al. (2020)). The less-than-expected relationship may be due to other signing reasons that are not fully captured by decarbonization motives.

Finally, US-domiciled funds are less likely to heavily decarbonize their portfolios, as indicated by the significant negative coefficient on the US (using Europe as the base case). This is in line with the common perception that there is a broader consensus around climate change in Europe compared to the US (e.g., Papadopoulos and Horster, 2019) and that the success of divestment is linked to the social norm in the market, which may be higher for Europe (e.g., Hong and Kacperczyk (2009)). Furthermore, the coefficients on the style dummies indicate that large-cap value, small-cap blend, and mid-cap blend funds (base case) are less likely to heavily decarbonize than the other styles.

### *4.5. Mutual fund decarbonization over time*

Next, we examined active mutual fund decarbonization over time. To do that, we analyzed the quarterly average active WACI change of decarbonizing funds identified in Section 4.4 displayed in Fig. 2. Decarbonizing funds most drastically reduced their WACI from one quarter to the next in Q2/2014, Q1/2016 and Q4/2016, as indicated by active WACI reduction. However, there is no clear link to political (e.g., COP- conferences) or natural climate events.

This observation is consistent with the view that mutual funds do not decarbonize in specific quarters but rather stretch decarbonization transactions over time to avoid implicit trading costs such as market impact or signaling. Fund managers may rather react to specific events by announcing and committing to decarbonization than by selling the stocks right away. In fact, there was a significant increase in decarbonization commitments after the COP 21 (Paris Agreement), when the number of committing institutions rose from 200 to 400.[11]

We do not observe an upward trend in this representation of active mutual fund decarbonization over time, which could have been expected from its growing popularity. This is mainly due to the measurement approach. The figure shows that decarbonizing funds actively reduced their WACI rather constantly by 40–50% on average. This matches the extent to which WACI reductions are easily achievable without larger modifications of the portfolio composition as suggested by the hypothetical decarbonization potential displayed in Fig. 1, constituting a quasi-natural upper barrier. Additional decarbonization efforts are represented by breaches of the barrier (e.g., Q2/2014, Q1/2016 and Q4/2016).

### *4.6. Stock-level decarbonization selling pressure*

After identifying and analyzing actively decarbonizing funds in the previous subsection, we continue by analyzing the trades of these funds. As we are interested in intentional decarbonization, we use two conservative restrictions to identify "decarbonization trades": 1) Only sell trades of the top 5 dirtiest holdings (before the trade) with respect to stock-level CI are considered. The identified stocks would be sold first to achieve decarbonization goals,

[11] Source: Gofossilfree (2019).

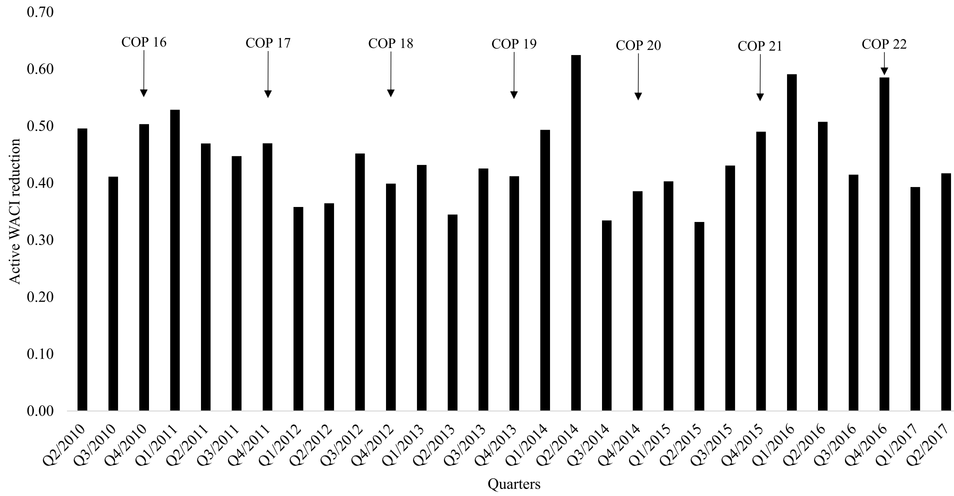



**Fig. 2.** Active WACI reduction by decarbonizing funds.
This figure plots the average WACI change in the lowest decile of active WACI change over time. *Active WACI change* reflects the proportion of funds' WACI which is actively reduced by shifts in portfolio weights in the respective quarter. In each quarter, we sort funds into deciles of active WACI change and refer to the fund quarters in the bottom decile as decarbonizing fund-quarters. The construction of *active WACI change* is described in Section 4.3.

as by selling these stocks, fund managers can heavily reduce the WACI without significantly altering the portfolio composition (see Section 4.2). 2) The trades must lead to a WACI reduction—that is, their stock-level CI must be greater than the pre-trade fund-level WACI. Following these restrictions, we identified 6.22% of all sell trades by actively decarbonizing mutual funds as intentional decarbonization trades.

To analyze divestment at the stock level, we once again follow Coval and Stafford (2007) and Khan et al. (2012) and contrast decarbonization trades with potentially opposing "carbonization trades", which we identified in a similar manner.[12] Then, we calculated our novel measure of quarterly stock-level "decarbonization selling pressure" (DSP) following Eq. (7) as the total number of shares sold in decarbonization trades minus the total number of shares bought in carbonization trades in quarter $t$, divided by the average number of shares traded from prior quarters ($t$–5 to $t$–2) in the overall market. For the following event study, we sorted stocks quarterly into deciles of DSP and referred to the top decile as "high DSP" (HDSP), which was thus our main treatment sample of divested stocks.[13]

$$DSP_{i,t} = \frac{\sum_j \max\left(0, -\Delta\ shares_{j,i,t}\right) | decarbonization\_trade_{j,i,t}}{Average\_shares\_traded_{i,t-5,t-2}} - \frac{\sum_j \max\left(0, \Delta\ shares_{j,i,t}\right) |\ carbonization\_trade_{j,i,t}}{Average\_shares\_traded_{i,t-5,t-2}} \quad (7)$$

To mitigate selection bias and to isolate the effect on stock prices by mutual fund decarbonization, we contrasted DSP with "general selling pressure" (GSP), which is derived from all trades not previously identified as decarbonization or carbonization trades. These included trades by the funds in deciles 2–9 of active WACI change plus the trades of the funds in deciles 1 and 10 that were not in the top 5 dirtiest holdings or which had a stock-level CI below the pre-trade WACI. GSP was calculated using Eq. (8). We sorted stocks quarterly into deciles of GSP and referred to stock-quarters in the top decile as an alternative treatment sample with "high GSP" (HGSP).[14]

$$GSP_{i,t} = \frac{\sum_j \Delta\ shares_{j,i,t} | neither\_decarbonization\_nor\_carbonization\_trade_{j,i,t}}{Average\ shares\_traded_{i,t-5,t-2}} \quad (8)$$

There was an intersection of 282 stock-quarters that qualified for both HDSP and HGSP. As we cannot be certain that these HDSP stocks are intentionally sold for decarbonization, we used a conservative approach and strictly defined those as HGSP. In addition, we introduced a control sample without treatment labeled "no selling pressure" (NSP) with the aim of comparing our results to stocks that showed no price pressure initiated by mutual funds. NSP was constructed from deciles 5 and 6 of GSP.

Table 2 reports the mean stock characteristics for the different treatment and control samples. The full sample includes 144,276 stock-quarters from Q2/2010 to Q3/2017. The HDSP sample consists of 969 stock-quarters, the HGSP sample consists of 14,056 stock-quarters and the NSP sample consists of 28,092 stock-quarters. Table 2 shows that the stock-level characteristics of the HDSP and HGSP samples are relatively similar except for the book-to-market ratio (BTM), stock-level CI, CI rank, DSP and GSP. Except for BTM, which is higher for HDSP stocks than for HGSP stocks, all other differences are due to the construction of the samples.[15]

## 5. The effect of mutual fund decarbonization on stock prices

### 5.1. Event study of HDSP, HGSP, and NSP stocks

We used an event study to analyze the price impact of DSP on stock prices, defining as "events" all stock-quarters for which

[12] At the fund level, actively "carbonizing funds" reflect the top decile of active WACI change. At the trade level and analog to decarbonization sell trades, two restrictions ensure that we only consider intentional carbonization: 1) Buy trades of the top 5 dirtiest holdings (after the trade), and 2) Stock-level CI greater than pre-trade fund-level WACI. In this way, we identify 6.18% of the trades by actively carbonizing funds as carbonization trades.

[13] $shares_{j,i,t}$ is the difference between number of shares held in $t$ minus numbers of shares held in $t$–1.

[14] We winsorize DSP and GSP at the 0.5% and 99.5% levels.

[15] The construction of HCI-HDSP and HCI-nonHDSP is described in Section 5.2.

**Table 2**
Characteristics of different stock samples.

| | Total sample | | HDSP | | HGSP | | NSP | | HCI-HDSP | | HCI-nonHDSP | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | N | Mean | N | Mean | N | Mean | N | Mean | N | Mean | N | Mean |
| 1-year prior return | 106,636 | 13.8% | 759 | 9.3% | 10,547 | 9.7% | 20,786 | 13.5% | 714 | 8.7% | 5,132 | 13.5% |
| BTM | 142,326 | 0.63 | 959 | 0.76 | 13,593 | 0.60 | 27,483 | 0.71 | 903 | 0.77 | 6,737 | 0.80 |
| Net sales (in $-billion) | 143,296 | 7.6 | 962 | 7.1 | 13,669 | 6.3 | 27,969 | 8.5 | 906 | 7.2 | 6,860 | 7.1 |
| Market cap (in $-billion) | 142,992 | 9.1 | 959 | 7.4 | 13,624 | 6.7 | 27,830 | 9.7 | 903 | 7.3 | 6,812 | 8.0 |
| Volatility | 127,447 | 16.8% | 870 | 16.1% | 12,276 | 16.8% | 24,504 | 17.4% | 820 | 16.1% | 6,016 | 19.9% |
| Stock-level CI | 144,276 | 0.03% | 969 | 0.32% | 14,056 | 0.02% | 28,092 | 0.04% | 913 | 0.34% | 6,899 | 0.20% |
| CI rank | 144,276 | 2,357 | 969 | 359 | 14,056 | 2,440 | 28,092 | 2,285 | 913 | 280 | 6,899 | 273 |
| DSP | 12,653 | 0.0% | 969 | 3.7% | 1,168 | 0.4% | 1,992 | −0.2% | 913 | 3.7% | 2,491 | −0.2% |
| GSP | 144,276 | −0.5% | 969 | −4.7% | 14,056 | 10.4% | 28,092 | −0.1% | 913 | −4.4% | 6,899 | −0.2% |

This table compares selected stock-level characteristics of the Total (144,276 stock-quarters), HDSP (969 stock-quarters), HGSP (14,056 stock-quarters), NSP (28,092 stock-quarters), HCI-HDSP (913 stock-quarters) and HCI-nonHDSP samples (6899 stock-quarters) for the survey period from Q1/2010 to Q3/2017. *1-year prior return* is the one-year return before the quarter. *BTM* is the year-end book-to-market ratio obtained from Refinitiv Datastream. *Net sales, Market capitalization* is year-end, displayed in $-billion, and obtained from Refinitiv Datastream. *Volatility* is the volatility of monthly returns over the total sample period. *Stock-level CI* is the ratio of year-end carbon emissions (scope 1 + 2) divided by year-end net sales. *CI rank* reflects the average rank of the samples if stocks are sorted in descending order according to their stock-level carbon intensity. *DSP* (*GSP*) reflects decarbonization (general) sell pressure. The construction of the HDSP, HGSP, NSP samples is described in Section 4.6 The construction of the HCI-HDSP and the HCI-nonHDSP sample is described in Section 5.2.

stocks are identified as HDSP, i.e., when they are in the top DSP decile. To ensure that the results were not driven by selection bias, we compared the cumulative abnormal returns before, during, and after the event for our treatment sample HDSP, the alternative treatment sample HGSP, and the untreated sample NSP. We calculated monthly industry-adjusted abnormal stock returns using the equal-weighted French-48-industry-portfolios following Khan et al. (2012).[16] The abnormal returns are then aggregated to portfolios in event time for the three samples.[17] To consider the long-term effects of divestment on stock prices, we consider a three-year period in total—12 months before until 24 months after the event—as the event window.

The event study result is plotted in Panel A of Fig. 3, where the small table within the figure reports the cumulative industry-adjusted returns over specific sub-periods. For the pre-event period [*t*–12; *t*–2], the figure indicates that there are no considerable abnormal returns for HDSP and NSP. However, the HGSP sample starts to accumulate negative abnormal returns of –2.5%. During the event quarter [*t*–1; *t*+1], both HDSP and HGSP showed considerable negative abnormal returns, while NSP showed no relevant change. The price decline during the event was much stronger for HDSP (–3.3%) than for HGSP (–1.9%).[18] In the post-event period [*t*+2; *t*+24], we observed no relevant cumulative abnormal returns for NSP, which remained at zero, and HGSP, which remained at the immediate post-event level. HDSP stocks, however, kept sloping downwards, gaining further negative cumulative abnormal returns of –3.4%. The total cumulative abnormal return of HDSP during and after being divested was –6.7%.

We can draw several conclusions from these results. First, the pre-event returns suggest that HGSP is partly predictable, as new financial information such as negative earnings announcements or profit warnings is often anticipated by market participants (Christophe et al. (2004)). This is apparently not the case for HDSP. Second, the price drop of HDSP and HGSP during the event quarter is consistent with studies by, e.g., Coval and Stafford (2007), Khan et al. (2012), Wermers (1999), and Ben-Rephael et al. (2011), who report that mutual funds can significantly affect stock prices if a critical mass of investors jointly sell their shares ("selling pressure hypothesis", Scholes (1972)).

Third, the observation that HGSP shows no relevant post-event abnormal returns mirrors expectations since the new financial information causing HGSP is efficiently priced by market participants (Coval and Stafford (2007)) and stock prices settle at a new level. Concerning the ongoing price decline of HDSP, the information triggering divestment does not contain fundamentally new information and is therefore not efficiently priced immediately after the event. Moreover, fund decarbonization communicates dissatisfaction with the environmental performance of divested firms, leading to a shift in stakeholders' perceptions (Dordi and Weber (2019); King and Soule (2007)). The fact that other market participants may herd into the decarbonization trades in subsequent periods (Benz et al. (2020)) may also help to explain why divested stocks' prices further decrease after the event.

### *5.2. Event study of HCI-HDSP and HCI-nonHDSP stocks*

As divestment mainly targets stocks with high CI, there is a possibility that our abnormal return patterns reflect a general price trend among carbon-intensive stocks. To rule out a possible selection bias, we sorted stocks quarterly into deciles depending on their stock-level CI and identified the top decile as "high carbon intensity" stocks (HCI). We created two subsamples: HCI stocks that are never strongly divested (HCI-nonHDSP) and HCI stocks that are strongly divested for at least one quarter (HCI-HDSP). Furthermore, we selected the HCI-HDSP sample in such a way that the stocks' average CI rank was similar to that of HCI-nonHDSP. To achieve this balance, we included further HDSP stocks from outside the top CI decile. Since HCI-nonHDSP shows a similar average CI rank but differs in terms of DSP, it presents an appropriate counterfactual to distinguish the effects of divestment from a general trend affecting all HCI stocks.

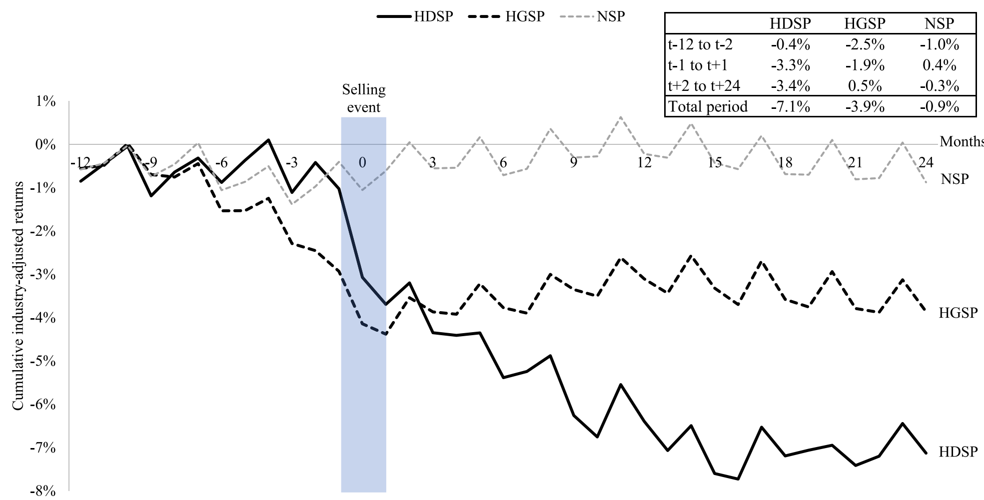
Table 2 shows the mean characteristics for the two samples. While the HCI-nonHDSP sample shows higher 1-year prior returns, the remaining statistics are relatively similar across the samples. Despite the selection criteria, there is a difference in stock-level CI (0.36% vs. 0.20%); however, the CI of both samples is very high compared to the "Total sample" average of 0.03%. Moreover, the difference in average CI ranks is very small, with the HCI-nonHDSP sample having on average a slightly higher rank (273 vs. 280). Both average ranks are higher than the average rank of the total HDSP sample (359).

[16] https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html. Industry-adjusted returns are winsorized at the 1% and 99%-level.

[17] Similar to Coval and Stafford (2007) we require at least 20 firms in a quarter for the firm average return to be included as an observation.

[18] Both numbers for HDSP and HGSP are statistically significantly different from zero (H0) at the 1% level based on the standard cross-sectional test by Boehmer et al (1991). For further evidence on significance, see Section 7.4.

*Panel A: HDSP, HGSP and NSP stocks*




*Panel B: HCI-HDSP, HCI-nonHDSP and HDSP stocks*

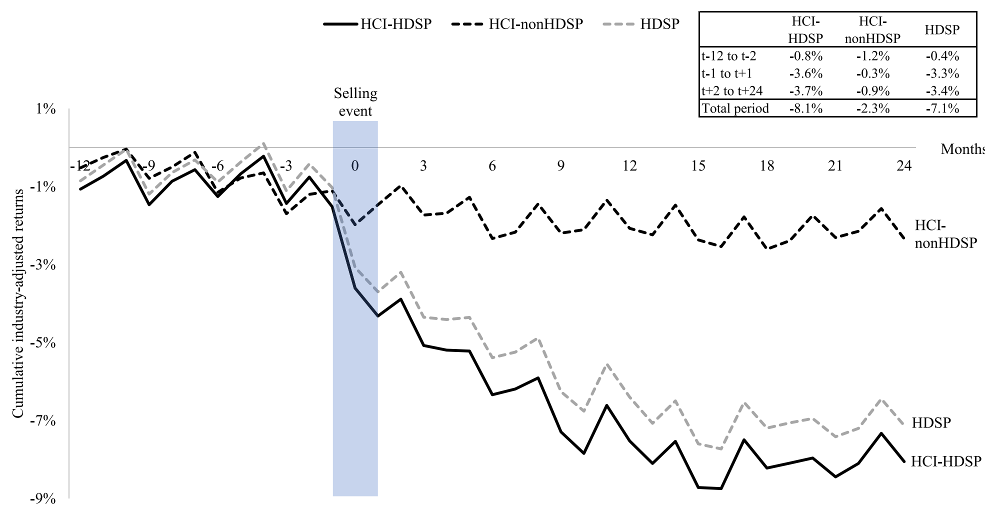



**Fig. 3.** Event studies on cumulative industry-adjusted returns.
This figure plots the cumulative average monthly industry-adjusted returns of different stock samples for the survey period from Q1/2010 to Q3/2017. The event quarter (t-1 to $t+1$) is the respective mutual fund heavy selling quarter. Monthly stock returns are adjusted using French-48-industry-portfolios as in Khan et al. (2012). Industry-adjusted returns are winsorized at the 1% and the 99% level. We sum average monthly industry-adjusted returns to obtain the cumulative average industry-adjusted returns. Panel A plots the HDSP, HGSP and NSP sample. Panel B plots the HCI-HDSP, HCI-nonHDSP and HDSP sample. *HDSP* (high decarbonization sell pressure) stocks represent the highly sold stocks due to decarbonization by mutual funds in the event quarter. *HGSP* (high general sell pressure) stocks represent the highly sold stocks due to other reasons than decarbonization by mutual funds in the event quarter. *NSP* (no sell pressure) stocks represent the stocks that were neither heavily bought nor sold by mutual funds in the event quarter. *HCI-HDSP* (high carbon intensity stocks with high decarbonization sell pressure) stocks represent stocks with high carbon intensities and additionally high decarbonization sell pressure by mutual funds in the event quarter. *HCI-nonHDSP* (high carbon intensity stocks with no high decarbonization sell pressure) stocks represent stocks with high carbon intensities and no high decarbonization sell pressure by mutual funds in the event quarter. The detailed construction of the stock samples is explained in Section 4.6 and 5.2. The HDSP (HGSP) [NSP] sample consists of 969 (14,056) [28,092] stock-quarters from 2010 to 2017. The HCI-HDSP (HCI-nonHDSP) sample consists of 913 (6,899) stock-quarters from 2010 to 2017.

Panel B of Fig. 3 plots the cumulative industry-adjusted returns for both samples. HCI-nonHDSP shows a moderately negative cumulative return over the whole event window, indicating a general downward price trend in HCI stocks. This downward trend amounts to −2.3% over the whole event window, of which −1.2% occurs before the event. HCI-HDSP stocks show a development very similar to HDSP stocks, with no relevant cumulative abnormal returns before the event but −7.3% over 26 months when divested [$t$−1; $t$+24]. These findings suggest that a general CI effect alone cannot explain the sharp price decline of divested stocks.

### 5.3. Calendar time panel regressions

To account for the difference in stock-level characteristics between the samples, we additionally run calendar time panel regressions explaining after-event cumulative industry-adjusted returns of all stocks with DSP, controlling for contemporary GSP, stock-level CI, pre-event financial performance, and further firm characteristics, as well as for firm and time-fixed effects. The variables of interest are standardized to a unit standard deviation to allow coefficient comparisons. All regressions account for clustered standard errors on the dimensions of firm and time.

**Table 3**
Calendar time panel regressions of cumulative industry-adjusted returns.

| Cumulative industry-adjusted returns | | | | | | | |
|---|---|---|---|---|---|---|---|
| | t0 | t0 to *t*+1 | t0 to *t*+3 | t0 to *t*+6 | t0 to *t*+10 | t0 to *t*+16 | t0 to *t*+24 |
| DSP | −0.004*** | −0.007*** | −0.008*** | −0.009*** | −0.011*** | −0.010*** | −0.007*** |
| | (−9.49) | (−11.45) | (−9.61) | (−8.13) | (−8.33) | (−6.43) | (−3.92) |
| GSP | −0.003*** | −0.004*** | −0.005*** | −0.005*** | −0.005*** | −0.006*** | −0.004** |
| | (−5.51) | (−5.88) | (−5.25) | (−4.74) | (−3.86) | (−3.53) | (−1.99) |
| Stock-level CI | −0.000 | −0.000 | 0.001 | 0.001 | 0.004 | 0.011*** | 0.017*** |
| | (−0.39) | (−0.14) | (0.43) | (0.56) | (1.48) | (3.32) | (4.24) |
| Past performance | −0.015*** | −0.028*** | −0.050*** | −0.087*** | −0.128*** | −0.202*** | −0.306*** |
| | (−8.72) | (−11.90) | (−15.45) | (−21.40) | (−26.18) | (−35.14) | (−45.57) |
| Constant | 0.001** | 0.002*** | 0.004*** | 0.005*** | 0.008*** | 0.007*** | 0.012*** |
| | (1.99) | (4.05) | (5.50) | (5.37) | (6.60) | (5.09) | (7.08) |
| Firm fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Time fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 37,497 | 37,497 | 37,497 | 37,497 | 37,497 | 37,493 | 34,411 |
| R-squared | 6.3% | 11.1% | 17.0% | 23.2% | 29.7% | 38.0% | 49.6% |
| Adjusted R-squared | 2.3% | 7.3% | 13.4% | 19.9% | 26.7% | 35.3% | 47.3% |

This table reports regression results on cumulative industry-adjusted returns for different holding time periods for the survey period from Q1/2010 to Q3/2017. We incrementally extend the time period and calculate cumulative stock returns starting with the middle month within the event quarter. We standardize DSP and GSP to unit standard deviation to ensure comparability of coefficients. *DSP* reflects stock-level decarbonization sell pressure. *GSP* reflects general sell pressure. *Stock-level CI* is the ratio of scope 1 + 2 carbon emissions divided by net sales. *Past performance* reflects the cumulative industry-adjusted returns of the 12 prior months. Standard errors are clustered by firm and time. T-statistics are presented in parentheses. *, **, *** denote significance on the 10%, 5%, and 1% level, respectively.

The results are presented in Table 3 and are in line with Fig. 3, in that stock-level CI has no effect in the short run and a positive effect on returns over the longer holding periods. In addition to this general effect of CI, DSP shows consistently negative, large and significant coefficients, confirming the negative price pressure resulting from mutual fund decarbonization. The coefficients generally increase with the length of the holding period, consistent with the downward slope of HDSP stocks displayed in Fig. 3. The GSP coefficients are also negative, consistent with the literature (e.g., Coval and Stafford (2007)) and with Panel A of Fig. 3. However, the coefficient is smaller than that of DSP and increases only slightly with the holding period. The coefficients on past performance are negative and significant. Therefore, stocks with negative returns after divestment had positive returns before divestment on average, which indicates that DSP is not systematically driven by poor past performance. This additional test thus confirms the results of both event studies presented in the preceding subsections.

## 6. The effect of mutual fund decarbonization on firms' carbon emissions

### 6.1. Event study of HDSP, HGSP, and NSP stocks

In the following, we examine whether the divestment pressure on stock prices we documented in Section 5 actually leads to changes in companies' CE. For this analysis, we made minor adjustments to our previous empirical setup. First, we used only the firm-reported CE from the three data providers CDP, Refinitiv, and Sustainalytics but no estimated CE, which may not adequately reflect CE *changes* over time (e.g., Kalesnik et al. (2020)). Second, we doubled the length of the event window to six years—24 months before until 48 months after the event—because it can be expected that investments in cleaner production technologies need time before taking measurable effect. Both adjustments reduce the number of observations relative to the analyses of cumulative abnormal returns.

Panel A of Fig. 4 shows an event study of the cumulative percentage changes in CE before and after divestment for the treatment sample HDSP, the alternative treatment sample HGSP, and the untreated control sample NSP. The CE of all three samples increased before the event. After the event, the CE of HGSP and NSP continued to increase. For NSP, this increase amounted to +8% over 48 months. HDSP stocks also kept increasing their CE after the event, but less steeply than before and well below the increase of the control samples. The cumulative CE change of HDSP peaks after 18 months and turns negative after 36 months, amounting to a cumulative CE decrease of –2.3% after 48 months. We repeat this event study using CIs instead and find similar results. The results are plotted in Panel A of Fig. A1 of the Internet Appendix.

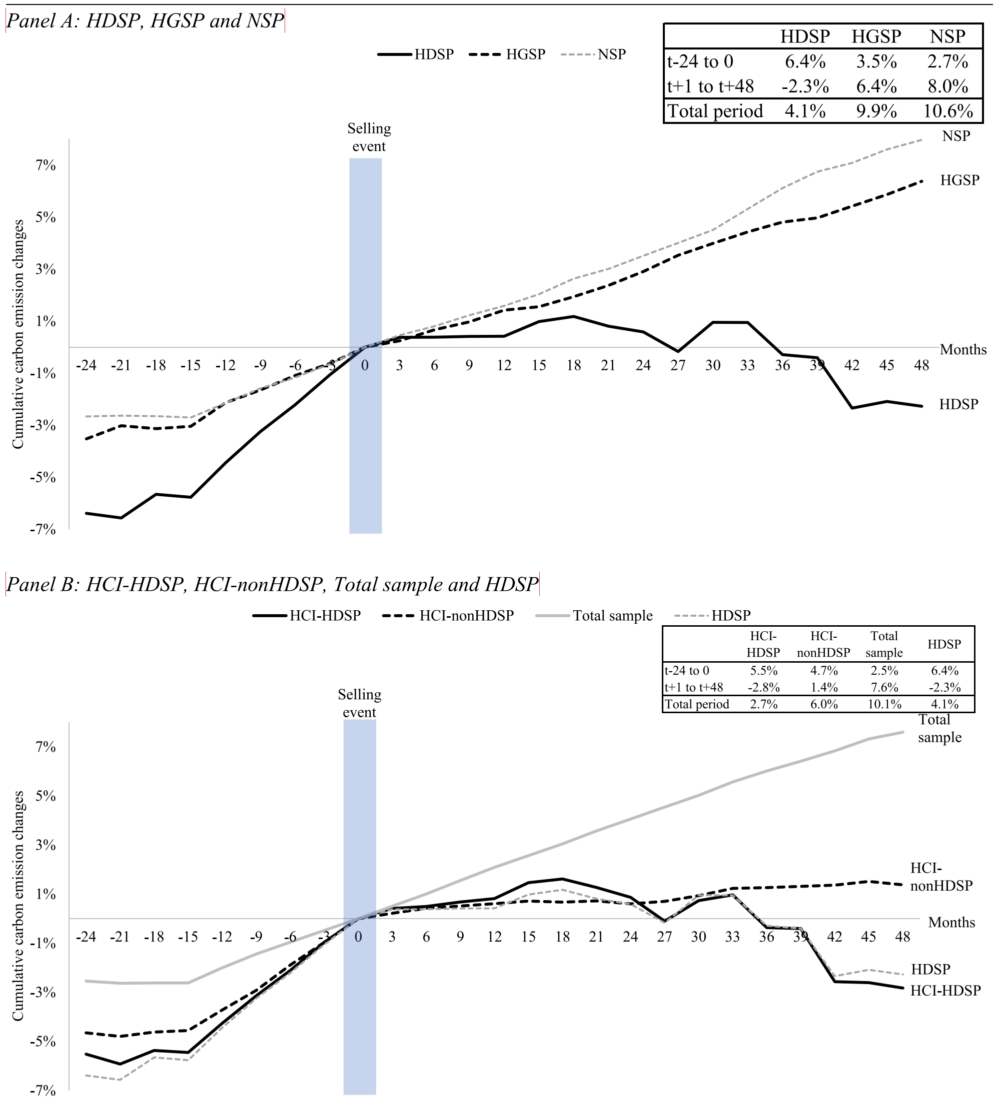
### 6.2. Event study of HCI-HDSP and HCI-nonHDSP stocks

The above finding may only reflect a general trend among HCI stocks to reduce CE more strongly relative to other firms for reasons other than being divested by mutual funds. Such reasons could be national regulations, international agreements, or overall energy or emissions markets. We therefore run another event study in Panel B of Fig. 4 to look at any differential patterns in cumulative CE changes of four samples: Total, HDSP, HCI-HDSP and HCI-nonHDSP.

"Total" confirms the overall trend that CE increases during our sample period (+10.1%). HCI-nonHDSP stocks show that there is indeed a general tendency of HCI stocks to reduce CE relative to other firms, as their cumulative CE increases only by +1.4% in the 48 months after the event. Similarly, HCI-HDSP stocks' cumulative CE changes also flattened after the event, thereby following this general trend. However, approximately 24 months after the event, their cumulative CE changes dropped below those of the HCI-nonHDSP stocks; after 36 months they dropped below zero, and after 48 months their cumulative CE changes amounted to –2.8%. In addition to CE, we repeat this event study using CIs instead and find similar results. The results are plotted in Panel B of Fig. A1 of the Internet Appendix.

### 6.3. Calendar time panel regressions

To further confirm these event study results, we run calendar time panel regressions of future cumulative CE changes of all companies on a dummy variable that indicates if DSP is positive (i.e., "Positive DSP") and on a dummy variable that indicates if the cumulative industry-adjusted return of the stock is negative




Panel A:

| | HDSP | HGSP | NSP |
|---|---|---|---|
| t-24 to 0 | 6.4% | 3.5% | 2.7% |
| t+1 to t+48 | -2.3% | 6.4% | 8.0% |
| Total period | 4.1% | 9.9% | 10.6% |

Panel B:

| | HCI-HDSP | HCI-nonHDSP | Total sample | HDSP |
|---|---|---|---|---|
| t-24 to 0 | 5.5% | 4.7% | 2.5% | 6.4% |
| t+1 to t+48 | -2.8% | 1.4% | 7.6% | -2.3% |
| Total period | 2.7% | 6.0% | 10.1% | 4.1% |

**Fig. 4.** Event studies on cumulative CE changes.
This figure plots the cumulative average percentage changes of carbon emissions of different stock samples over months for the survey period from Q1/2010 to Q3/2017. The event quarter (t-1 to $t$+1) is the respective mutual fund heavy selling quarter. Carbon emission changes are winsorized at the 1% and the 99% level. We sum average carbon emission changes to obtain the cumulative average changes. Panel A plots the HDSP, HGSP and NSP sample. Panel B plots the HCI-HDSP, HCI-nonHDSP and HDSP sample. *HDSP* (high decarbonization sell pressure) stocks represent the highly sold stocks due to decarbonization by mutual funds in the event quarter. *HGSP* (high general sell pressure) stocks represent the highly sold stocks due to other reasons than decarbonization by mutual funds in the event quarter. *NSP* (no sell pressure) stocks represent the stocks that were neither heavily bought nor sold by mutual funds in the event quarter. *HCI-HDSP* (high carbon intensity stocks with high decarbonization sell pressure) stocks represent stocks with high carbon intensities and additionally high decarbonization sell pressure by mutual funds in the event quarter. *HCI-nonHDSP* (high carbon intensity stocks with no high decarbonization sell pressure) stocks represent stocks with high carbon intensities and no high decarbonization sell pressure by mutual funds in the event quarter. The detailed construction of the stock samples is explained in Section 4.6 and 5.2. The HDSP (HGSP) [NSP] sample consists of 969 (14,056) [28,092] stock-quarters from 2010 to 2017. The HCI-HDSP (HCI-nonHDSP) sample consists of 913 (6,899) stock-quarters from 2010 to 2017.

over the 6 months after the event (i.e., "Negative post-event return"). Furthermore, we included an interaction of the two dummies to determine whether high DSP and a subsequent stock price decline coincided, indicating a divestment-related increase in cost of capital. In terms of the theoretical equilibrium framework of Heinkel et al. (2001), both divestment and a strong stock price decline must coincide to exceed the cost of reforming and thus create incentives for firms to reform. Furthermore, we controlled for GSP, both alone and interacted with the negative post-event return dummy, for the firms' CE level, for cumulative CE changes in the previous two years, and for cumulative pre-event industry-adjusted returns. Finally, we included after-event changes in net sales to account for changes in production output or changes in the carbon efficiency of production. The regressions were run both pooled and with firm and time fixed effects. All regressions accounted for clustered standard errors on the dimensions of firm and time.

The results reported in Table 4 support our previous event study findings. Specifically, the interaction term between positive DSP and negative post-event return yields negative coefficients in all but the last regression, suggesting that affected companies react to divestment in the desired way by reducing their CE relative to the control sample of non-divested companies. As expected, neither of the dummies alone leads to a reduction in CE, consistent with the equilibrium predictions of Heinkel et al. (2001).

With regard to the control variables, the coefficient on the level of CE is negative and often significant, consistent with the overall finding that HCI stocks generally reduce CE relative to low CI stocks. Companies whose CE had been increasing more strongly in

**Table 4**
Calendar time panel regressions of cumulative CE changes.

| Cumulative CE changes | $t$+3 to $t$+24 | $t$+3 to $t$+24 | $t$+3 to $t$+36 | $t$+3 to $t$+36 | $t$+3 to $t$+48 | $t$+3 to $t$+48 |
|---|---|---|---|---|---|---|
| Negative post-event return (t0 to $t$+5) | −0.007 | −0.001 | −0.001 | 0.006 | 0.003 | 0.003 |
| | (−0.51) | (−0.07) | (−0.04) | (0.51) | (0.15) | (0.20) |
| Positive DSP | 0.079*** | 0.052*** | 0.126*** | 0.058*** | 0.177*** | 0.041** |
| | (4.85) | (6.74) | (6.19) | (5.16) | (8.09) | (2.73) |
| Negative post-event return : Positive DSP | −0.056*** | −0.037*** | −0.081*** | −0.042*** | −0.107*** | −0.027 |
| | (−4.03) | (−3.73) | (−4.51) | (−3.28) | (−5.70) | (−1.65) |
| Positive GSP | 0.039*** | 0.005 | 0.068*** | 0.008** | 0.091*** | 0.007** |
| | (5.02) | (1.31) | (7.46) | (2.23) | (8.44) | (2.14) |
| Negative post-event return : Positive GSP | −0.027*** | −0.007 | −0.039*** | −0.009** | −0.048*** | −0.011** |
| | (−4.09) | (−1.69) | (−4.44) | (−2.13) | (−4.54) | (−2.60) |
| Current CE level | −0.000*** | −0.000* | −0.000** | −0.000 | −0.000** | −0.000 |
| | (−3.89) | (−1.73) | (−2.76) | (−1.44) | (−2.53) | (−1.65) |
| Cumulative CE change (t–24 to t–1) | 0.020** | −0.336*** | 0.041*** | −0.437*** | 0.049*** | −0.476*** |
| | (2.51) | (−12.42) | (3.47) | (−17.53) | (3.33) | (−10.81) |
| Cumulative return (t–15 to t–1) | 0.082*** | 0.043*** | 0.121*** | 0.034*** | 0.151*** | 0.025** |
| | (8.97) | (5.24) | (12.54) | (3.05) | (13.43) | (2.56) |
| Cumulative net sales change ($t$+3 to ...) | 0.000** | 0.000 | 0.000** | 0.000 | 0.000* | 0.000 |
| | (2.35) | (1.39) | (2.18) | (1.19) | (2.11) | (1.58) |
| Constant | 0.037** | 0.111*** | 0.033 | 0.166*** | 0.031 | 0.234*** |
| | (2.21) | (12.15) | (1.58) | (13.78) | (1.38) | (15.09) |
| Firm fixed effects | No | Yes | No | Yes | No | Yes |
| Time fixed effects | No | Yes | No | Yes | No | Yes |
| Observations | 191,641 | 191,548 | 155,193 | 154,814 | 123,551 | 123,406 |
| R-squared | 1.8% | 43.5% | 2.4% | 62.0% | 2.8% | 77.9% |
| Adjusted R-squared | 1.8% | 40.6% | 2.4% | 59.9% | 2.8% | 76.4% |

This table reports panel regression results of cumulative carbon emissions changes in the months subsequent to the analyzed quarter for the survey period from Q1/2010 to Q3/2017. We incrementally extend the time period and calculate cumulative carbon emission changes starting three months after the analyzed quarter. *Negative post-event return* is a dummy variable that is 1 if a company has negative cumulative industry-adjusted returns within and the five months following the analyzed quarter. *Positive DSP* is a dummy variable that is 1 if a company has positive decarbonization sell pressure in the analyzed quarter. *Negative return post-event return: Positive DSP* is a dummy variable that is 1 if a company has negative cumulative industry-adjusted returns within and the five months following the analyzed quarter and positive decarbonization sell pressure in the analyzed quarter. *Positive GSP* is a dummy variable that is 1 if a company has positive general sell pressure in the analyzed quarter. *Negative post-event return : Positive GSP* is a dummy variable that is 1 if a company has negative cumulative industry-adjusted returns within and the five months following the analyzed quarter and positive general sell pressure in the analyzed quarter. *Current CE level* represents the amount of carbon dioxide equivalents emitted in metric tons. *Cumulative CE change* is the cumulative relative change in carbon emissions eight quarters prior to the analyzed quarter. *Cumulative return* is the change in cumulative industry-adjusted returns five quarters prior to the analyzed quarter. *Cumulative net sales change* is the change in cumulative net sales subsequent to the analyzed quarter. Standard errors are clustered by firm and time. T-statistics are presented in parentheses. *, **, *** denote significance on the 10%, 5%, and 1% level, respectively.

the past reduced their CE more strongly afterward. Higher cumulative past returns, indicating a better expected business outlook, lead to an increase in CE. Finally, the constant is positive and statistically significant, consistent with the general increase in CE over our sample period shown for the total sample in Panel B of Fig. 4. Overall, the analysis in this subsection thus confirms our previous event study result, namely, that the decarbonization activities of mutual funds may indeed have a positive effect on the climate by motivating companies to reduce CE beyond the general pressure to reduce CE put on HCI firms by national and international legislation and adverse changes in energy and emissions prices.

## 7. Alternative explanations and robustness checks

### 7.1. Shareholder intervention

In our main analysis, we tried to eliminate many sources of endogeneity and selection bias; however, the question of whether divestment and mutual fund portfolio decarbonization are the cause of our observed effects still prevails. Therefore, this section tests alternative explanations and presents further robustness checks. One alternative explanation could be shareholder intervention—that is, shareholders putting pressure on firms to invest in cleaner production by engaging with companies and exercising their voting rights (Broccardo et al. (2020)). There is some academic evidence that climate-related shareholder intervention may have an effect on companies (e.g., Naaraayanan et al. (2020); Chu and Zhao (2019); Akey and Appel (2020)). In this context, filing shareholder proposals is a popular way for investors to express dissatisfaction with the environmental behavior of a firm. To consider shareholder interventions, we collected publicly available data on climate change-related shareholder proposals from four major shareholder proposal databases: Ceres, Proxy Monitor, ShareAction, and Refinitiv EIKON.[19] In total, we observed 639 climate change-related shareholder proposals over our sample period in the US and Europe, 35 of which coincided with an HDSP stock-quarter.

We accounted for shareholder intervention by excluding the 35 HDSP stock-quarters. We repeated our event study from Panel A of Fig. 3 by contrasting cumulative abnormal returns of HDSP, HDSP without shareholder intervention, and HGSP and found that shareholder intervention had little effect on our main results. Likewise, we repeated our event study from Fig. 4 by contrasting cumulative CE changes of the respective samples. HDSP and HDSP without shareholder intervention show virtually the same development, indicating that concurrent intervention had little effect on our results. The same applies for the event studies of HCI-HDSP versus HCI-nonHDSP. The modified event study on cumulative abnormal returns can be found in Fig. A2 of the Internet Appendix, and the modified event studies on CE changes are shown in Fig. A3 of the Internet Appendix.

[19] https://www.ceres.org/networks/ceres-investor-network/shareholder-resolutions-database, https://www.proxymonitor.org, https://shareaction.org/fossil-fuels/resolutions-tracker/.

We further confirm this by including the number of filed climate-related shareholder proposals received as an additional control variable in our panel regressions of cumulative industry-adjusted returns (Table 3) and cumulative CE changes (Table 4). The regression results are displayed in Table A6 of the Internet Appendix. The coefficients on our main variables remain virtually unchanged in all tested specifications. The coefficient on shareholder intervention is also negatively related to changes in CE. In economic terms, the event of portfolio decarbonization combined with a negative post-event return is related to a 5.5% lower cumulative CE change over the next 24 months on average relative to the general trend. Independent from that, each climate-related shareholder proposal is associated with a 2.4% lower cumulative CE change on average (see column 1). However, shareholder intervention only has a significant effect in model specifications which do not control for firm and time fixed effects. Overall, shareholder intervention is thus no alternative explanation for our results but has an additional positive effect on CE.

### 7.2. Decarbonization-unrelated price pressure

Another alternative explanation for high selling pressure on carbon-intensive stocks could be financial underperformance that coincides with divestment. In our main analysis, we controlled against this apprehension by only counting stock-quarters as HDSP if they did not experience high non-carbon-related GSP at the same time. Furthermore, in our calendar time panel regressions, we controlled for pre-event returns, which had no effect on the results. However, a direct test could provide further confidence in our findings. Therefore, we obtained data on earnings from Refinitiv EIKON and analysts' earnings forecasts from I/B/E/S and define an earnings surprise as a percentage deviation of more than 20% from the average of analysts' forecasts (Kinney et al. (2002)). Furthermore, we obtained profit warning releases from Refinitiv Datastream.

We incorporated these data into our empirical framework by excluding 1) 45 HDSP stock-quarters that coincided with an earnings surprise, 2) 101 HDSP stock-quarters that coincided with a profit warning, and 3) 142 HDSP stock-quarters that coincided with either an earnings surprise or a profit warning. We contrasted cumulative abnormal returns of HDSP, HDSP without earnings surprise and/or profit warnings, and HGSP in Fig. A4 of the Internet Appendix. We found that while earnings surprises and profit warnings slightly amplify the negative abnormal return development of HDSP stocks, the main findings remain intact in that divested stocks come under long-term price pressure. Thus, earnings surprises and profit warnings are not alternative explanations for our main results.

A further alternative explanation for systematic selling pressure on certain stocks could be that these stocks are delisted from a reference index (Harris and Gurel (1986)). While we concentrated on actively managed funds, which do not have to rebalance to index reconstitutions or at least have major discretion over how and when to rebalance, some unintentional WACI changes caused by index rebalancing may be falsely interpreted as intentional decarbonization. Therefore, we obtained information on index delisting via Refinitiv EIKON for 11 popular international stock indices covering 74.6% of the stocks held by our sample funds.[20]

We used these data to exclude all potential rebalancing trades from the calculation of funds' WACI changes and reclassified the fund-quarters previously identified as actively decarbonizing funds (bottom decile of active WACI change). However, the overlap of our main classification with the reclassification is 98.9%. Furthermore, excluding stock-quarters from HDSP that coincide with an index delisting only concerned 5 of 969 cases and did not alter our event study results on cumulative abnormal returns (Fig. A5 of the Internet Appendix). Finally, we include a delisting dummy in our panel regressions of cumulative abnormal returns, and our results remained intact (Table A7 of the Internet Appendix). Thus, index reconstitutions are not alternative explanations for our main results.

[20] S&P500, Dow Jones 30, EUROSTOXX50, FTSE100, Nikkei 225, DAX30, CAC40, TSE300 composite, SENSEX, Hang Seng, and All Ordinaries.

### 7.3. Unintentional decarbonization

In our main analysis, we identified intentional decarbonization as fund-quarters in the bottom active WACI change decile and concentrated on the trades of these fund-quarters to identify single decarbonization trades for the calculation of DSP. In addition, we excluded stock-quarters from HDSP if they also qualified for HGSP. While we are confident that this conservative approach mitigated unintentional decarbonization, some uncertainty remains as to how sustainable the decarbonization activities are. If, for instance, the WACI reduction is very short-lived, it may not have been intentional in the first place.

Therefore, we tracked the WACI development of fund-quarters in the bottom active WACI change decile and only counted those fund-quarters as decarbonizing in which the WACI did not rebound beyond the immediate post-decarbonization WACI [$t$+1] by the end of the event window [$t$+24]. This very conservative restriction eliminated 32% of the HDSP sample. We repeated our event study of cumulative abnormal returns contrasting HDSP, long-term HDSP, and HGSP. We found that our main result remains economically unchanged. The only slight difference is that long-term HDSP experiences a small negative abnormal return before the event. The event period returns and long-term development, however, are similar to those of HDSP. The results are plotted in Fig. A6 of the Internet Appendix.

### 7.4. Event study drawbacks and cross-sectional diff-in-diff regressions

Throughout our empirical analysis, we rely mainly on graphical event studies. While we support and confirm all the results using additional calendar time panel regressions, we consider it important to discuss potential event study drawbacks. Choosing an appropriate counterfactual to the treatment is important for an event study to allow for interpretations that go beyond correlation. In most event studies of cumulative returns (CR), the usual counterfactual is the cumulative return of the market or of a specific industry, resulting in cumulative abnormal returns (CAR), which are then tested against the hypothesis that the event causes zero CAR (Eq. (9)).[21]

$$CAR^{HDSP} = \overline{CR}_i^{HDSP} - \overline{CR}_i^{\text{Industy}} \tag{9}$$

In addition to cumulative abnormal returns, we contrast our treatment sample HDSP with the untreated sample NSP. Thus, following Eq. (10), our empirical setup resembles a cross-sectional difference-in-differences (DID) analysis.[22]

$$\begin{aligned} DID^{HDSP,NSP} &= \left(\overline{CR}_i^{HDSP} - \overline{CR}_i^{\text{Industy}}\right) - \left(\overline{CR}_j^{NSP} - \overline{CR}_j^{\text{Industry}}\right) \\ &= \overline{CAR}_i^{HDSP} - \overline{CAR}_j^{NSP} \end{aligned} \tag{10}$$

[21] E.g., with the Boehmer et al (1991) standard cross-sectional test, see footnote 18.

[22] The standard DID analysis includes universal pre- and post-treatment periods and thus a time-series dimension. As our divestment events are distributed over the sample period only the cross-sectional dimension remains. We account for the time dimension by running the cross-sectional regression in multiple event-time windows around the divestment.

**Table 5**
Cross-sectional Double Diff-in-Diff (DDID).

Panel A: Cumulative industry-adjusted returns

| | Cumulative abnormal returns | | | Chi² tests | | |
|---|---|---|---|---|---|---|
| | Pre-Event [t-12; t-2] | Event [t–1; t+1] | Post-Event [t+2; t+24] | Pre-Event vs. Event | Pre-Event vs. Post Event | Event vs. Post-Event |
| HDSP | 0.003 | −0.029*** | −0.034*** | 14.58*** | 11.25*** | 0.21 |
| | (0.49) | (−7.02) | (−3.95) | | | |
| HGSP | −0.017*** | −0.019*** | 0.006 | 0.08 | 12.54*** | 14.06*** |
| | (−4.05) | (−8.30) | (1.45) | | | |
| $Chi^2$ tests (H0: HDSP - HGSP = 0) | 14.06*** | 10.92*** | 22.46*** | | | |
| Constant | −0.001 | 0.001 | 0.004 | | | |
| | (−0.22) | (0.25) | (0.52) | | | |
| N | 110,347 | 110,347 | 110,347 | | | |
| Adjusted $R^2$ | 0.1% | 0.4% | 0.0% | | | |

Panel B: Cumulative CE changes

| | Cumulative CE changes | | Chi² tests |
|---|---|---|---|
| | Pre-Event [t–24; t–1] | Post-Event [t0; t+48] | Pre-Event vs. Post Event |
| HDSP | 0.002 | −0.074*** | 16.74*** |
| | (0.15) | (−4.57) | |
| HGSP | 0.006 | −0.002 | 0.64 |
| | (1.21) | (−0.25) | |
| $Chi^2$ tests (H0: HDSP - HGSP = 0) | 0.11 | 10.97*** | |
| Constant | 0.052*** | 0.087*** | |
| | (12.17) | (12.50) | |
| N | 9,321 | 9,321 | |
| Adjusted $R^2$ | 0.00% | 0.09% | |

This table shows the results of cross-sectional difference-in-differences regressions of cumulative abnormal returns (Panel A) and cumulative carbon-emissions changes (Panel B) on dummies for HDSP and HGSP stock-quarters in event time during the survey period from Q1/2010 to Q3/2017. The event window of 36 months in Panel A (72 months in Panel B) is split into specific sub-windows pre [$t$–12; $t$–2], during [$t$–1; $t$+1], and post event [$t$+2; $t$+24] (pre [$t$–24; $t$–1] and post [$t$0; $t$+48]). The sub-windows regressions are run simultaneously via seemingly unrelated regressions. Coefficient identity within and between sub-windows are tested via $Chi^2$-tests. T-statistics are presented in parentheses. Standard errors are clustered by month. *, **, *** denote significance on the 10%, 5%, and 1% level, respectively.

Further contrasting HDSP with the alternative treatment HGSP resembles a cross-sectional double difference-in-difference (DDID)—that is, an indirect comparison between the two treatments via the common untreated sample NSP. The same applies to the comparison of HCI-HDSP with the two counterfactuals HCI-nonHDSP and NSP in Panel B of Fig. 3.

$$DID^{HGSP,NSP} = \left(\overline{CR}_n^{HGSP} - \overline{CR}_n^{Industry}\right) - \left(\overline{CR}_j^{NSP} - \overline{CR}_j^{Industry}\right) = \overline{CAR}_n^{HGSP} - \overline{CAR}_j^{NSP} \tag{11}$$

$$DDID^{HDSP,HGSP} = \left(\overline{CAR}_i^{HDSP} - \overline{CAR}_j^{NSP}\right) - \left(\overline{CAR}_n^{HGSP} - \overline{CAR}_j^{NSP}\right) = \overline{CAR}_i^{HDSP} - \overline{CAR}_n^{HGSP} \tag{12}$$

To account for this resemblance and test for significant differences between the treatment and control samples, we designed a regression-based cross-sectional DID. Specifically, we pooled the CAR of HDSP, HGSP and NSP in specific event-time windows and explained them with dummies indicating HDSP and HGSP. The constant $b0$ of this regression represents the average CAR of the NSP sample, the slope coefficients $b1$ and $b2$ represent the average CAR differences of HDSP and HGSP to NSP, and the difference between the slope coefficients $b1$ – $b2$ represents the average CAR difference between HDSP and HGSP. $ei$ is a mean zero error term.

$$CAR_i = b_0 + b_1 D_i^{HDSP} + b_2 D_i^{HGSP} + e_i \tag{13}$$

To mitigate another typical drawback of an event study—the short-term focus—we defined three subperiods during the event windows for the calculation of CAR. These are analogous to those in the event-study figures, i.e., the months pre [$t$–12; $t$–2], during [$t$–1; $t$+1], and post divestment [$t$+2; $t$+24]. To account for intertemporal dependencies and to be able to test for coefficient differences between the sub-periods, we ran the three cross-sectional regressions simultaneously as seemingly unrelated regressions. The regression results are presented in Panel A of Table 5.

The results in Panel A clearly confirm the graphical results in Panel A of Fig. 3. Before the event, HDSP shows no CAR difference from NSP, while HGSP had already accumulated some significantly negative CAR. The difference between the treatment samples is significant as well. In the event, both treatment samples showed a significantly negative CAR difference from NSP; however, HDSP showed a significantly more negative CAR than HGSP. After the event, HDSP continued to show a long-term negative CAR difference from NSP, while HGSP increased slightly. The difference between HDSP and HGSP is significant. Over time, the coefficients on HDSP during and post-event are not significantly different, confirming the ongoing price decline. Conversely, the coefficients of HGSP during and post-event are significantly different, confirming that the new information is quickly and adequately priced and does not lead to further price declines. However, the coefficients are not statistically significant prior to and during the event, confirming the anticipation of the information by market participants.

Panel B of Table 5 presents similar seemingly unrelated cross-sectional regressions explaining cumulative CE changes of HDSP, HGSP and NSP during the two sub-periods before [$t$–24; $t$–1] and after the event [$t$0; $t$+48]. The results clearly confirm the graphical results in Panel A of Fig. 4. In the pre-event period, the increase in CE of HDSP and HGSP was not statistically different. However, in the post-event period, HDSP showed a significantly lower CE increase than both NSP and HGSP. Over time, HDSP clearly and significantly changes their CE relative to NSP, while HGSP shows no statistically significant difference between the sub-periods. Overall, these seemingly unrelated cross-sectional regressions thus confirm and strengthen our main event study findings while simultaneously addressing the usual drawbacks and criticisms of event studies in general.

## 8. Conclusion

The important question of whether divestment from carbon-intensive firms' stocks can measurably contribute to the global war against climate change is highly debated among academics, practitioners, and policy-makers. This is because the link between investors divesting from carbon-intensive stocks and firms reducing their CE is indirect. In between those steps, the stock price must decrease due to selling pressure before firm managers react by lowering emissions. Several theoretical equilibrium models have demonstrated this causal chain, beginning with Heinkel et al. (2001). Although proving its existence is not a trivial task, we find cautious but consistent empirical evidence of such a causal chain. It begins with portfolio decarbonization decisions of mutual funds and ends with decreasing CE of the divested firms.

We developed a novel approach to identify decarbonization trades by mutual funds and applied it to a large and unique combined dataset of US and European equity mutual fund holdings and global firm-level CE. This approach resulted in our main new measure of funds' *decarbonization selling pressure* (DSP) on firms' stock prices. Then, we applied the measure to our global firm-level dataset and tested whether high DSP translates into the depressed stock prices intended by the divestment movement and whether the combination of DSP and stock price decline results in lower CE by the divested firms. Our empirical investigations using graphical and regression-based event studies as well as alternative calendar-time panel regressions showed statistically significant positive evidence in both cases. Firms divested by mutual funds show strong and sustainable stock price declines, on average. Moreover, divested firms, which experience such a stock price decline, reduce their CE on average compared to non-divested firms, which on average increase their CE during our sample period.

To allow for cautious causal interpretations of these results, we intensively controlled for different sources of endogeneity and selection bias during our investigation. First, to ensure that our results were not driven by other concurrent sources of price pressure, we contrasted our main treatment sample of divested firms against an untreated control sample of firms without selling pressure as well as against an alternative treatment sample of firms with high general selling pressure from sources unrelated to mutual fund decarbonization. In additional tests, we directly controlled for selling pressure due to earnings surprises and profit warnings as well as index reconstitutions. Moreover, we incorporated controls for pre-divestment financial performance, which could be a reason for systematic selling pressure, in our calendar-time panel regressions.

Second, we want to ensure that our results are not endogenously driven by a general downward trend in stock prices and CE of HCI firms, e.g., stemming from carbon-related changes in legislation or adverse price developments in energy and emissions markets. Therefore, we contrasted our main treatment sample of divested firms against an untreated but similar control sample of other HCI firms that have never been strongly divested by the mutual funds in our sample. In additional tests, we also directly controlled for other sources of decarbonization pressure, such as direct shareholder intervention. Furthermore, we tested for concurrent changes in the sales revenues of the divested firms, which could be driving the reduction in CE, in our calendar-time panel regressions. As a result, our main treatment sample of divested firms behaved very differently from all of the control and alternative treatment samples. Furthermore, none of the additional control variables and test designs and none of the alternative explanations diminished our results. Overall, we are confident that a cautious causal interpretation of our findings is warranted. Our findings are in line with theoretical predictions; however, due to a lack of previous research, we cannot relate our findings to other empirical studies of actual divestment. We advocate for increasing research efforts regarding the impact of investor actions on the climate-related behavior of companies. Moreover, the question of whether the effect of mutual fund decarbonization on the CE of the divested firms in our sample has a measurable effect on climate change—that is, how strongly it contributes to achieving the 1.5 °C target established by the Paris Agreement—is beyond the scope of this study and awaits future research. Additionally, a comparison to the effectiveness of other shareholder actions, such as shareholder engagement, and investigations of further effects of divestment, such as board and management changes or enhanced climate-related disclosure, should be subjects of future research. However, our findings do show that divestment can be an effective tool that private, institutional, and public investors can use to motivate carbon-intensive firms to reduce their CE and accelerate the transition to a global low-carbon economy if the divestment is focused and targeted as a critical mass of investors applying the necessary decarbonization pressure.

## CRediT authorship contribution statement

**Martin Rohleder:** Conceptualization, Methodology, Funding acquisition, Supervision, Project administration. **Marco Wilkens:** Conceptualization, Methodology, Funding acquisition, Supervision. **Jonas Zink:** Conceptualization, Methodology, Funding acquisition, Data curation, Software.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## Appendix - List of abbreviations

This appendix lists the abbreviations used throughout the article.

| Abbreviation | Explanation |
|---|---|
| *General* | |
| AUM | Assets under management |
| BTM | Book-to-market ratio |
| CDP | Carbon Disclosure Project |
| CR | Cumulative returns |
| CAR | Cumulative abnormal returns |
| CE | Stock-level carbon emissions |
| CI | Stock-level carbon intensity |
| PDC | Portfolio Decarbonization Coalition |
| TCFD | Task Force on Climate-related Financial Disclosures |
| WACI | Weighted average carbon intensity |
| *Construction of stock samples* | |
| DSP | Decarbonization sell pressure |
| GSP | General sell pressure |
| HDSP | High decarbonization sell pressure sample |
| HGSP | High general sell pressure sample |
| NSP | No sell pressure sample |
| HCI | High carbon intensity stocks |
| HCI-HDSP | High carbon intensity and high decarbonization sell pressure sample |
| HCI-nonHDSP | High carbon intensity and no high decarbonization sell pressure sample |

## Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.jbankfin.2021.106352.

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