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Marco Ceccarelli

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General introduction and summary of results

A large part of human anguish and suffering is rooted in societal issues that stem from a lack of sustainability, either a social one or an environmental one. Financial markets – and in particular institutional investors, professional asset managers that exert discretion over large amounts of capital – have a special responsibility. Through channeling a large amount of capital, institutional investors have the power to change the behavior of corporations and, in this way, alleviate social and environmental issues.

This dissertation begins by exploring how institutional investors voice their preferences for firms that exploit the regulatory environment more or less aggressively. These institutions play an important role in influencing corporate policies: As owners, their duty is to ensure that their firms operate optimally, traditionally equated with maximal profits. However, from a broader point of view, this is not necessarily beneficial for society. To attain such performance, corporate managers could tweak financial statements, window-dress earnings, or move revenues to tax havens.

The first chapter, "Walk the line - Do investors reward firms that exploit regulatory gray areas?" demonstrates that some institutional investors indeed have preferences for firms that refrain from exploiting regulation aggressively. This is particularly the case for "Dedicated" institutions, long-term investors that hold a limited number of firms and are not susceptible to current earning news. I identify trust as a channel that drives this finding: When investors realize the value of trust, e.g., after a case of financial adviser misconduct at their firm, they significantly reduce their exposure to firms that exploit regulation aggressively. Finally, this chapter shows that investors' preferences matter – not only for asset allocation decisions – but also influence firms' behavior. After a merger, a new institutional investor takes over the portfolio firms of its target. Then, these firms change their behavior to cater to the preferences of their new owner.

Certainly, the actions of institutional investors are meaningful, but what measures can we take to "improve" their behavior? What steps should society take to make institutional investors more sustainable? Chapter 2, "Low-carbon mutual funds", explores the effects of disclosing new information in the form of a low-carbon label on the climate performance of mutual funds' portfolios.

First, we describe the risk profile of funds labeled as low-carbon. These funds display a potentially lower exposure to the future realization of climate risks but, since they underweight "dirty" sectors, they have higher idiosyncratic volatility relative to the current market portfolio. In other words, low-carbon funds offer a trade-off between lower climate risk and worse diversification.

How do investors react to this trade-off? We find a strong preference for climate-friendly funds, leading us to conclude that being low carbon improves a fund's ability to attract investments. The reaction of investors does not fall on deaf ears. Fund managers that did not receive the low-carbon designation at its introduction later improved their sustainability credentials.

Disclosing new information about the sustainability of investors' portfolios appears to be an effective tool for nudging fund managers towards becoming more climate-friendly. However, portfolio rebalancing – selling firms whose sustainability performance lags behind that of their peers and buying better performing firms instead – is not necessarily the best way to improve the overall sustainability of the economy. Ideally, sustainability-oriented investors would remain invested in lagging firms and push them to improve. The last chapter of the dissertation, "Can asset managers attract assets by disclosing superior ESG practices?", asks if there is an appetite for a more holistic form of disclosure by asset managers.

We use the institutional setting of the Principles of Responsible Investment (PRI), the world's largest responsible investment network. After joining, institutional investors are obligated to file an annual report, which is then assessed and scored by the PRI. This is, to our knowledge, the only standardized reporting framework focused on sustainability issues. Some topics covered by the report are stock selection and investor engagement, compensation of executives, the appointment of portfolio managers, and organizational ESG resources.

We obtain access to these scores and show that institutional mutual fund investors reward institutions with higher scores on the reporting framework. The reaction is particularly strong when sustainability ratings verified by Morningstar confirm the high scores that are voluntarily disclosed.

Taken together, the findings presented in this thesis offer some hope that society is moving toward solving some of its most pressing issues. There are long-term, dedicated institutional investors that actively express a preference for firms wary of exploiting regulatory loopholes. Fund managers are willing and able to adjust their portfolio allocations towards climate-friendly firms when their clients can easily voice a preference for such investments. Finally, investors do not care exclusively about investors' portfolio allocation but are also concerned with more holistic sustainability disclosures.

This said, there are many more issues that we need to solve if we want to achieve a smooth transition towards a low-carbon, more equal, and generally more sustainable economy. I hope that finance scholars will – together with policymakers – address these problems more vehemently in the future.

Walk the line

Do investors reward firms that exploit regulatory grey areas?

Marco Ceccarelli*

June 14, 2021

Abstract

This paper investigates whether certain investors either prefer or dislike holding firms that exploit more of the available regulatory wiggle room and if such a strategy pays off. Exploited wiggle room (WR) is captured by relatively aggressive tax planning, financial reporting, and earnings management practices. I find that long-term, low-turnover investors hold firms with 3% higher exploited WR than those held by short-term, high-turnover investors. After experiencing financial adviser misconduct that breaches their trust, investors reduce the exploited WR of their holdings by 5%. This is consistent with investors choosing firms according to their preferences for WR. The preferences of investors also impact firm behavior. Overall, investors seem to have heterogeneous preferences for WR exploitation and a liking for cautious firms that cannot be explained by a profit maximization motive alone.

JEL Classifications: G23, G4, M41.

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1 Introduction

A substantial part of the economy is controlled by institutional investors, such as mutual funds, insurance companies, pension funds, banks, and hedge funds. The academic literature has extensively discussed the impact that institutional ownership has on firms covering topics from R&D investment (Bushee, 1998) and monitoring (Chen, Harford, and Li, 2007) to transparency (Boone and White, 2015) and CSR policy (Dyck, Lins, Roth, and Wagner, 2018).

Much less attention has been directed towards understanding the *revealed preferences of the institutional investors themselves*: What can be learned from the observed portfolio allocations? Do investors also care about other aspects besides their performance? Specifically, does it matter to them *how the firms they hold achieve their results?* This paper is the first to investigate differences in investor preferences for firms that aggressively exploit regulatory *"wiggle room"* (WR). I posit that all firms have to some degree a freedom of choice, a leeway, or wiggle room that they can exploit within acceptable corporate practices, before entering illegal territory. WR exploitation is identified on the firm level by relatively aggressive tax planning, financial reporting, and earnings management practices. To obtain the implied preferences of institutional investors, I adapt the methodology of Gibson, Krueger, and Mitali (2021): I download the quarterly portfolio holdings from the Thomson 13F database, and then compute for every quarter the weighted average of exploited WR in each investor's holdings, the *"portfolio wiggle room"* (PWR).

It could be the case that some institutional investors prefer *"aggressive firms"* that exploit WR to a great extent, whereas others are more keen to hold *"cautious"* firms that do not exhaust WR. As it is not ex ante clear that this should be the case, the first question this paper asks is whether institutional investors differ significantly with respect to their preferences for WR. The second question asks if institutional investors' preferences influence firm behavior. Finally, do these preferences affect portfolio performance? Answering these questions is crucial for at least two reasons: First, the growing interest in the "purpose" of institutional investors (Fink, 2018) discounts the implications of heterogeneity in the degree to which firms abide by regulation. Some institutional investors could actively facilitate the exploitation of regulatory loopholes, thereby creating an "unfair" comparative advantage for their portfolio firms. Second, via portfolio allocation choices, investors could "nudge" firms into a more or less exploiting behavior, which can have important externalities, e.g., on market transparency.

In summary, I find that dedicated investors hold firms that exploit 5% less wiggle room than those held by the average quasi-indexer. Furthermore, institutional investors significantly reduce their PWR after they fire one of their financial advisers due to a misconduct disclosure. This suggests that a shock to the perceived value of trust produces a shift in the preferences of institutional investors for WR exploitation. The preferences of institutional investors also appear to have important implications for firm behavior. After a merger between two investors occurs, the firms in the portfolio of the target change their behavior to cater to the preferences of the acquiring party. Finally, I find that investors with smaller PWR achieve somewhat higher alphas but are more exposed to idiosyncratic risk. Taken together, it seems that institutional investors have heterogeneous preferences for regulatory wiggle room exploitation, which cannot be fully rationalized by a profit maximization motive alone: Investors who hold cautious firms seem to also care *how* the performance is achieved, especially so when they deem trust to be especially valuable.

To better understand the mechanisms that could explain the findings, this paper seeks to answer three broad questions: *Why* should institutional investors have different preferences for WR and do these preferences matter for firm behavior? Do these differences have *performance implications*? Intuitively, different strategies could drive heterogeneity: Investors that have short horizons and rebalance their portfolios often will prefer firms that are more transparent, as this will enable better informed trading. Market conditions could also play a role regardless of investment strategy: Baker and Wurgler (2007) argue that when sentiment is high, investors tend to prefer more "speculative" and therefore opaque securities. I expect that short-term and high-turnover investors will hold firms with lower WR. I also expect that when market sentiment is high, all investors will tend to hold firms with higher WR (*Hypothesis 1 - Transparency*).

Second, heterogeneity in preferences can also be a consequence of structural differences amongst investors: Those that are subject to public scrutiny (e.g.: banks, insurance companies, or pension funds) should prefer holdings with small WR (*Hypothesis 2 - Scrutiny*). This is because firms that are overly aggressive in exploiting the regulatory environment, could be managed by "suspect CEOs", and therefore also be more likely to get involved in scandals and illegal behavior (Biggerstaff, Cicero, and Puckett, 2015; Cline, Walkling, and Yore, 2018).

Finally, investors that are "dedicated" - i.e., that have a long-term horizon, are undiversified, and not susceptible to current earning news (Bushee, 1998) - could prefer firms that do not fully exhaust WR (*Hypothesis 3 - Trust*). Honesty is fundamental for trust to develop among people (O'Neill, 2002), and trust in management improves employee satisfaction (Dirks and Ferrin, 2002), which in turn has a positive long-term impact on overall firm performance (Edmans, 2011). A CEO that does not exploit WR could be perceived as more honest and trustworthy (Gibson, Sohn, Tanner, and Wagner, 2017). Since this channel is likely to be most effective in the long-run, it should be most relevant for dedicated investors as they take a holistic view on their holdings. One way to test this is to exploit a plausibly exogenous shock to the perceived importance of trust. Gennaioli, Shleifer, and Visgny (2015) show theoretically and Gurun, Stoffman, and Yonker (2017) confirm empirically that the relationship between an investor and her advisor crucially relies on trust.

In this spirit, a financial adviser that discloses a case of misconduct (Egan, Matvos, and Seru, 2019) could breach the trust of the investor that employs him. This can be seen as a shock to the investor's perceived importance of trust that would induce a change in her preference for wiggle room exploitation. I expect investors who experience misconduct to shift their portfolios towards more cautious firms. On related lines, Lins, Servaes, and Tamayo

(2017) and Amiraslani, Lins, Servaes, and Tamayo (2017) show that being trustworthy will be deemed as more valuable during turbulent periods of high uncertainty. Thus I expect that when market uncertainty becomes extreme all investors will tend to prefer firms with lower WR.

The second question this paper addresses is whether differences in WR preferences have investment performance implications. Exploiting regulatory leeway can cause financial gains, e.g., by decreasing the effective tax rate (Bird and Karolyi, 2017) or by (barely) beating analysts' earnings forecasts (Bhojraj, Hribar, Picconi, and McInnis, 2009). Therefore, I expect that the portfolios of investors who tend to hold aggressive firms will generate higher returns (*Hypothesis 4 - Performance*). Lastly, high WR firms have, to some extent, more alleys available to conceal poor results. This would allow them to smooth performance more, something valued by both management (Fudenberg and Tirole, 1995) and investors (Rountree, Weston, and Allayanis, 2008). Therefore, having higher PWR should be correlated with less stock price volatility (*Hypothesis 5 - Risk*).

The sample used to test these hypotheses is retrieved from the Thomson 13F database (CDA/Spectrum) and spans 1995 to 2019, totaling more than 100,000 quarterly observations of 8,000 investors. These represent all US firms and advisers with assets under management exceeding USD 100mm.

In order to assess WR exploitation at the individual holdings level, I use several proxies: (1) earnings management (Jones, 1991; Dechow, Sloan, and Sweeney, 1995; Kothari, Leone, and Wasley, 2005), (2) disaggregation quality of financial statements (Chen, Miao, and Shelvin, 2015), (3) long-term effective cash tax rate (Dyreng, Hanlon, and Maydew, 2008), (4) discretionary permanent tax differences (Frank, Lynch, and Rego, 2009), (5) subsidiaries in tax haven countries (Dyreng and Lindsey, 2009), and (6) beating the median consensus earnings forecast by no more than one USD cent (Bhojraj et al., 2009). To identify aggressive firms, I construct percentile rankings of (1) - (4) for every industry-year combination. For (5) I resort to a within industry-year indicator that captures above average tax shelter usage;

(6) is directly computed as an indicator. Finally, the basic proxy for exploited WR is the average of (1) to (6).

Institutional investors are classified on the basis of: (1) investment horizon in short- and long-term (Cremers and Pareek, 2015); (2) rebalancing activity in low- and high-turnover (Carhart, 1997); (3) investment strategy in quasi-indexers, transient, and dedicated investors (Bushee, 1998); (4) fiduciary duties in banks, pension funds, insurers, investment firms, and advisers (Bushee, 2001). Finally, to assess portfolio performance I compute quarterly excess returns, portfolio alphas (Fama and French, 1996), and exposure to idiosyncratic volatility (Ang, Hodrick, Xing, and Zhang, 2006). I extract the revealed preferences of investors through a value weighted average of the exploited WR of their portfolio holdings, i.e., *"portfolio wiggle room"* (PWR).

In support of *Hypothesis 1 - Transparency* I find that a short-term horizon is associated with a 0.9% smaller PWR compared to an average investor. This number is 1.2% smaller for frequent traders. This suggests that investors who hold stocks for shorter periods, and trade more, value the increased transparency of cautious firms. Market conditions also play a role: A one standard deviation (0.6) increase in market sentiment is associated with an increase in average PWR of 0.5 percentage points (pp). When sentiment is high, institutional investors tend to prefer firms that are more aggressive and thus opaque, as these may also appear as more speculative.

My findings contradict *Hypothesis 2 - Scrutiny*, since the average exploited PWR of banks and public pensions is slightly higher *higher* than that of miscellaneous investors. This suggests that exposure to public scrutiny is not enough to make investors prefer holding cautious firms.

I can confirm *Hypothesis 3 - Trust*: Dedicated investors have a PWR 1.8 percentage points smaller (34% of a standard deviation) than investors closely following an index. The trust channel seems to be most important for holistic and specialized investors, with particularly long-term horizon. However, when market conditions become particularly volatile, all investors tend to hold more cautious firms. This suggests that being cautious is particularly valuable during periods when the overall level of trust in financial markets is low. Moreover, an institutional investor will lower its PWR by over 4pp after she fires a financial adviser who discloses a case of misconduct. This change is economically significant and does not revert in the three years after the disclosure. When the perceived value of being honest and trustworthy increases, investors will prefer firms that are more cautious and that do not overly take advantage of the regulatory environment.

These preferences have important consequences for firm behavior. After a merger between two institutional investors occurs (Lewellen and Lowry, 2021), the acquiring institutions press forwards with their preferences. I look at firms where the target investor was a blockholder, holding at least a 5% stake or being one of the five largest owners. These firms significantly change their behavior after a merger, reducing the difference between their exploited wiggle room and that of the acquirer by 1.2 percentage points in the 2 years after the merger.

Finally, my findings contradict *Hypothesis 4 - Performance*: PWR is unrelated to excess returns, but negatively related to portfolio alphas: A one standard deviation increase in PWR is associated with a decrease in portfolio alpha of 0.1pp. Additionally, there is a positive relationship between PWR and portfolio risk: A one standard deviation increase in PWR implies a smaller exposure to idiosyncratic risk of 15.3% of a standard deviation, which supports *Hypothesis 5 - Risk*.

Overall, there seem to be systematic differences in investors' preferences for regulatory WR, which cannot be fully explained by different risk-return profiles: Some investors appear to not only care about the performance per se, but also about the way this performance is achieved; particularly so when their trust has been recently broken.

This paper complements the literature that analyzes the interplay between personal values and investment behavior. Among the first, Hong and Kacperczyk (2009) uncover the existence of "sin" stocks in the market, and Hong and Kostovetsky (2012) find that political orientation influences investment choices. Gibson et al. (2021) examine the relationship between investors' horizon and CSR preferences. This study adds to this literature by showing that there are also more subtle dimensions of investor tastes: Independent of industry, the degree to which firms exploit regulation also influences portfolio allocation. Not only what results are achieved, but also *how* these are achieved seems to matter to institutional investors.

2 Sample construction and methodology

First, I show how the proxy for wiggle room (WR) exploitation is constructed and how it is used to obtain the revealed preferences of institutional investors. Then I present the methodology for classifying institutional investors and computing their performance measures. Finally, I briefly describe the control variables. Table 1 contains an overview of all the variables that are presented in this section. Summary statistics on a firm and institutional investor level are presented in Tables 2 and 3. The sample used covers the entire Compustat and I/B/E/S universe for the periods between 1995 and 2019, totalling over 130,000 firm-year pairs.

- Table 1 -

2.1 Proxying for regulatory wiggle room exploitation

I posit that there are different dimensions along which a firm can exploit regulatory WR before committing illegalities, amongst which are financial reporting, earnings management, and tax planning. Below I discuss the individual proxies and how they capture "aggressive" and "cautious" firm behavior, i.e., how I identify firms that exploit WR to a great extent and those that do so only to a small extent.

The extent of detail with which a firm presents its financial results is measured by the disaggregation quality (DQ) of financial statements proposed by Chen et al. (2015). If a firm wants to hide poor performance or worrisome positions, it will tend to aggregate several balance sheet items or income statement lines which reduces DQ. Having a lower disaggregation quality will capture more aggressive financial reporting practices.

Earnings management (EM) is measured via discretionary accruals, which are the main mechanism through which firms can artificially improve performance and smooth earnings. Discretionary accruals are defined as the difference between total (actual) and expected accruals. Whilst there are also further ways to manage earning, e.g., changes in accounting methods, big bath accounting (Burgstahler and Dichev, 1997) etc., I resort to discretionary accruals, as they are comparatively easy for an outsider to measure. As there is no consensus regarding the best model of expected accruals, I follow Eugster and Wagner (2018) and compute an average of the proxies proposed by Dechow et al. (1995), Jones (1991), and Kothari et al. (2005). Having larger discretionary accruals will capture more aggressive earnings management.[1]

An additional signal of a firm exploiting regulatory WR is when the reported quarterly earnings barely beat the forecast of analysts. This is captured as Bhojraj et al. (2009) propose, namely via an indicator for firms that beat the median consensus forecast by no more than 1 USD cent. The consensus forecast is computed on the basis of the I/B/E/S unadjusted detail file to control for rounding errors (Payne and Thomas, 2003).

I capture aggressive tax planning activities through different proxies. First, the long-term cash effective tax rate (CashETR) proposed by Dyreng et al. (2008) measures the average cash taxes a firm paid over the past five years. A firm that consistently has a relatively low tax rate is deemed aggressive. Frank et al. (2009) propose an alternative measure to capture tax aggressiveness: They first compute the expected permanent differences in total book taxes and then interpret the residual as discretionary permanent difference (DTAX). The larger DTAX of a firm is, the more aggressive its tax planning activities are. I use both measures as the first could be potentially coined as overly simplistic since it does not explicitly identify avoidance activities. The second suffers from a joint hypothesis problem, as

[1] One concern that arises from accrual modelling is the positive correlation between the estimated abnormal accruals and the firm's actual accruals (Dechow, Ge, and Schrand, 2010, p. 358).

there is no consensus structural model which explains differences between book and effective tax rates (Hanlon and Heitzman, 2010, p. 142).

Finally, firms also have the possibility to move revenues to subsidiaries in tax haven countries. I capture this corporate practice by retrieving the number of such subsidiaries a given firm has from Scott Dyreng's website (Dyreng and Lindsey, 2009) and scale this by the logarithm of total assets. The larger this figure is, the more aggressive a firm is deemed to be.

2.2 Aggregating the individual wiggle room exploitation proxies

It is not ex-ante clear which threshold a firm needs to reach before its behavior can be classified as either aggressive or cautious. It could be that for each industry there is a different such cutoff, as various business models allow for different degrees of exploitation. Additionally, this cutoff is bound to change over time as first, new regulation comes into force and second, changing conditions and market perceptions make some practices become warranted. Such time trends can also have a differential impact on firms operating in different industries. Below I propose a method of aggregating individual proxies that accounts for these issues.

First, I rank firms within a given industry-year according to each proxy of WR exploitation and assign to each firm percentile values. The only exceptions are the indicator for barely beating analysts' forecasts and the number of subsidiaries in tax haven countries. The former practice can be considered to be equally questionable across time and industries. For the latter, I resort to a within-group average as a cutoff, as more than half of the firm-years have zero subsidiaries in tax haven countries. The main measure for WR is then computed as a simple average of these percentile rankings and the two indicators. In this way I obtain a continuous proxy for more or less regulatory exploitation within a given industry-year: Cautious firms will have small WR and aggressive firms large WR.

In untabulated results I replicate all findings with an alternative measure for WR: Instead of using a continuous proxy, one can identify aggressive firms by an indicator value that uses the 75th percentile as a cutoff.[2]

Summary statistics of both individual proxies and the wiggle room measures are presented in Table 2. The distribution of firm-level WR is slightly left skewed and has almost no excess kurtosis. WR is scaled by construction between 0 and 1. Since data requirements vary between the different proxies, I can only compute a median number of 4 (out of a total of 6) WR proxies for each firm-year pair. Correlations between individual proxies are reported in Appendix Table A1 and are surprisingly low, suggesting that the practices captured are intrinsically different.

- Table 2 -

2.3 The revealed preferences of institutional investors

To extract the revealed preferences of investors, I adapt the methodology developed by Hwang, Titman, and Wang (2017) and Gibson et al. (2021). In a first step, I download the holdings of institutional investors from Thomson 13F (CDA/Spectrum) database. This covers quarterly portfolio allocation of all US investors that have assets under management in excess of 100,000 USD. My sample starts in 1995Q1 and ends in 2017Q4, totaling over 150,000 observations.[3]

I merge the firm-level WR exploitation measure (on average available for 90% of the quarterly holdings) to the dataset containing holdings of institutional investors. Then, I compute the weighted average for every quarterly portfolio, which yields the main measure of interest, exploited portfolio wiggle room, PWR. A higher PWR indicates that an investor is "aggressive", i.e., that she holds firms in her portfolio that are, on average, more exploitative.

[2] I also consider extracting principal components of the indicators. This approach is not attractive: First, using as many as three components would only capture about 50% of the cumulative variation. Second, the eigenvalues of the components are relatively small, with the largest being close to one.

[3] WRDS recognized a major issue in the Thomson data feed starting from 2012 and provides researchers with direct access to the SEC filings of institutional investors. Thus, part of the sample is directly downloaded from the SEC and then aggregated according to the methodology proposed by WRDS to emulate the Thomson data.

2.4 Classifying institutional investors

In the first part of the paper, I want to test whether there is a systematic relationship between investor type and preferences for regulatory wiggle room exploitation. To do so, I classify investors along several dimension. First, I compute investors' portfolio duration (Cremers and Pareek, 2015, p. 1660). This measure captures the weighted average number of quarters an investor holds a stock in her portfolio over the past five years. I classify investor horizon as short-term if the portfolio duration in a given quarter is below the 25th percentile (3.2 quarters), and long-term if it is above the 75th percentile (8.1 quarters).

An alternative, albeit related classification, is obtained by measuring quarterly portfolio turnover, as discussed in Carhart (1997). This measure captures the percentage of assets under management that an investor sells or buys (depending on which is smaller) in a given quarter. It is computed as the absolute value of the minimum of quarterly sales and buys, divided by the average assets under management in the current and previous quarter. I differentiate between low and high turnover, i.e., between investors in the top quartile (below 3.3%) and the last quartile (above 16.5%). Whilst conceptually similar to duration, turnover is a more transient measure centered around trading behavior, whereas duration takes an arguably more long-term perspective. The correlation between the two measures is -55.2% as investors who trade more and have higher turnover also tend to hold their stocks for a shorter period.

Additionally, I download the investor classifications proposed by Bushee (2001) to differentiate along legal types and general investment strategies. First, I can distinguish between banks, corporate and public pension funds, insurance companies, endowments, and miscellaneous investors. The investment strategy is captured via a cluster analysis along the dimensions of horizon, turnover, and specialization. Three strategies are then defined: transient (TRA) investors, with short horizon, high turnover, and high diversification; dedicated (DED) investors, with long horizon, low turnover, and high concentration, and quasi-indexers (QIX) with long horizon, low turnover, and high diversification (Bushee, 2001, p. 214). The main caveat of this approach is that the vast majority of investors are classified as quasi-indexers (55.9%) or transient (39.2%). Also, since the data Bushee provides ends in 2015Q4, I extend the last available classification to the remaining observations, which may introduce noise in the data.

2.5 Portfolio performance of institutional investors

In the second part of the analysis I want to test whether observed differences in portfolio wiggle room (PWR) are correlated with heterogeneity in performance. To be able to do this, I measure portfolio performance and risk respectively via excess quarterly returns and portfolio alphas, and via exposure to idiosyncratic risk.

Since I observe only quarterly snapshots of the asset allocation of institutional investors, I assume that all trades occur at the end of a given quarter. Raw portfolio returns are the weighted average of returns generated by the end-of-quarter holdings. This approach is routinely used in the literature but ignores all trades that occur within a quarter. However, at least for the subset of mutual funds, the resulting return differential is close to zero (Kacperczyk, Sialm, and Zheng, 2008, p. 2380). To obtain excess portfolio returns I subtract the quarterly treasury rate from the raw returns and then winsorize at the 1% level.

I control for both exposure to the quarterly returns of the 3-factor (Fama and French, 1996) and the 5-factor (Fama and French, 2015) Fama-French (FF) portfolios. This is done via an overlapping rolling window regression over the past 12 quarters with factor returns downloaded from the website of Kenneth French. Quarterly alphas are the intercept of these regressions. I compute idiosyncratic risk exposure as the standard deviation of the residuals of the FF regressions (Ang et al., 2006, p. 283).

2.6 Control variables

To account for possible confounding effects I control for several variables: the logarithm of assets under management, the logarithm of the number of different stocks in the quarterly holdings, an indicator variable for holdings focusing on no more than two different industries, and the number of quarters an investor is in the sample. All regressions also account for time-invariant factors through quarter fixed effects. The observations are likely to exhibit correlation both across time on the individual institutional investor level and in the cross-section since during any given quarter all investors hold stocks from the same universe (Seasholes and Zhu, 2010, p. 1989). Therefore, it is crucial to allow for multi-way clustering of standard errors in the empirical tests which is done following the approach proposed by Cameron, Gelbach, and Miller (2011).

2.7 Summary statistics

Summary statistics for all variables at an institutional investor level are presented in Table 3. I observe the average investor for about 59 quarters. Exploited PWR is on average 39% and has a standard deviation of 5%. The distribution exhibits an excess kurtosis of about 5, which implies that there are several investors that shift their holdings respectively towards aggressive and cautious firms.

- Table 3 -

In Figure 1 I explore whether there have been any time trends in the preferences of institutional investors for regulatory wiggle room exploitation. I plot both the average investor-level PWR and the average firm-level WR. It appears that overall, institutional investors tend to hold firms that are more aggressive than the average. This tendency has been disappearing, as the spread between average PWR and firm-level WR started narrowing after 2001. A possible explanation for this reversal is that following the adoption of regulation Fair Disclosure in August 2010, institutional investors lost their preferential access to insider information and had to rely on publicly available information instead (Ke, Petroni, and Yu, 2008). This, in turn, could have made more cautious and transparent firms more attractive.[4]

[4]Interestingly, there has been an upward trend in wiggle room exploitation from 2017 onwards, driven mainly by earnings and tax management. One explanation might be the election of Donald Trump in 2016 and the resulting tax reforms (Wagner, Zeckhauser, and Ziegler, 2018).

- Figure 1 -

3 Heterogeneity of preferences for portfolio wiggle room

In this section, I examine whether institutional investors exhibit heterogeneity in their preferences for regulatory wiggle room exploitation and look at why this could be the case. Exploiting regulatory wiggle room to a great extent could make a firm less transparent, more likely to get involved in corporate scandals and illegal behavior, and reduce the amount of trust that employees have for its management.

I posit that these potential implications will matter more to some investors than to others. I hypothesize that this effect will be systematically related to investors' characteristics, namely heterogeneity in the need for transparency, in fiduciary duties, and in the value investors place on trustworthiness. To see whether this is the case, I study differences in preferences for wiggle room exploitation along investment horizons and trading behavior, as well as along the legal types of investors and their general investment strategies. Finally, I use the disclosure of financial adviser misconduct as an exogenous shock to investors' preferences. After such events, the importance of trust will become salient and the exposed investors will place a higher value on trustworthiness.

3.1 Investment horizon and portfolio turnover

Previous research has argued that, overall, institutional investors prefer holding firms with higher disclosure quality, because by doing so the liquidity of their holdings improves and information asymmetries decrease which reduces overall transaction costs (Diamond and Verrecchia, 1991). However, this channel will matter less to investors that have a long-term horizon and trade less. These investors will have more opportunities to interact with firms' management and gather private information which will give them a comparative advantage over less informed traders (Edmans and Manso, 2011, p. 2396). Short-term investors and frequent traders will be more concerned about the ease with which information can be obtained and the transaction costs caused by their trades (Boone and White, 2015, p. 509). Since aggressively exploiting wiggle room will make firms less transparent, I expect the PWR of investors to be positively correlated with investment horizon and negatively correlated with turnover (*Hypothesis 1 - Transparency*).

I test this in Table 4 by respectively regressing quarterly PWR on an indicator for short- and long-term investment horizon and on one for high and low portfolio turnover. The models (1) and (4) include only the baseline regressions that control for assets under management, portfolio diversification, number of quarters a given investor is in the sample, and exposure to the FF 3-factor portfolios. The average exploited PWR of the benchmark categories for horizon is 39.0% and for turnover it is 39.1%. The coefficients reveal that investors with a short-term horizon and a high turnover have a PWR about 1% smaller than the benchmark ($\frac{-0.362}{39.0}$ and $\frac{-0.463}{39.1}$). This means that short-term and high turnover investors tend to prefer firms that are more cautious; both these findings support *Hypothesis 1 - Transparency.* The coefficients of the control variables are in line with expectations: Higher exposure to the high-minus-low, market, and small-minus-big portfolios is associated with smaller PWR. This is first because firms that are smaller tend to exploit wiggle room less. Second, the market average of exploited WR is smaller than that of institutional investors' portfolios. Therefore, increasing exposure to the market will correlate to a reduction in PWR. The proxies for investor size and specialization are (mostly) insignificant.

Models (2) and (4) additionally control for the volatility of the individual investors' PWR, as it could be that the average stability of PWR is inherently linked to its level. The results are almost identical to the previous columns.

- Table 4 -

In unreported analyses, I test whether the relationship between the preferences for PWR and investment horizon remains significant when portfolio turnover is included in the regression. I find that the coefficient of the long-term dummy remains significant and similar in size while that of the short-term dummy becomes insignificant. This suggests that long-term investors prefer more aggressive firms because they are better able to gather insider information which gives them a comparative advantage. It seems that trading activity is the main reason why short-term investors prefer more cautious firms.

Finally, including the continuous measures for investment horizon and portfolio turnover instead of dummies leaves the results unchanged. When I additionally control for turnover squared, it has a positive coefficient: The same decrease in trading intensity is associated with a much larger increase in PWR when the reference point is a low turnover portfolio than it would be the case for a high turnover portfolio. It seems that decreasing PWR beyond a certain point will not yield additional informational benefits.

3.2 Legal type and strategy

Previous research has found that several of the firm-level proxies that I use to construct the measure of exploited wiggle room are associated with illegal firm practices: Aggressive earnings management and just beating analysts' forecasts are both an indicator for "suspect firms", i.e., firms that are more likely to engage in financial reporting fraud (Biggerstaff et al., 2015, pp.107-110). Moreover, O'Donovan, Wagner, and Zeume (2018) exploit the 2016 leak of the Panama Papers to show that subsidiaries in tax haven countries are associated with both bribery and tax evasion. I therefore posit that firms that exploit regulatory wiggle room to a large extent could be more likely to get involved in illegal activities or corporate scandals. I hypothesize that one channel that explains investors' preferences towards more or less aggressive firms is their legal type. This is because the standards of prudence that regulatory authorities require from institutional investors are heterogeneous: Banks have the most stringent ones, followed by pension funds, and lastly mutual funds and other investment advisers who are relatively unconstrained (Del Guercio, 1996, pp. 33-36). I expect investors with more stringent fiduciary duties to be more concerned about the possibility of litigation and therefore to prefer firms that exploit regulatory wiggle room less (*Hypothesis 2* -

Scrutiny).

I test this hypothesis in Table 5, where in columns (1) to (3) PWR is regressed on a dummy for investor's legal type using miscellaneous investors as the benchmark. Model (1) indicates that most legal types do not exhibit significant differences when compared to miscellaneous investors. Only banks and public pensions tend to hold portfolios of firms that are significantly more aggressive. Model (2) additionally controls for the volatility of PWR which has little impact on the magnitude of the coefficients. This contradicts *Hypothesis 2 - Scrutiny*, as it suggests that having stronger fiduciary duties does not correlate with a preference for more cautious firms. It could be that these investors have an informational advantage when compared to other institutional investors, and therefore also tend to hold firms that are less transparent.If so, this additionally supports *Hypothesis 1 - Transparency*.

It is likely that the general investment strategy of investors will also influence their preferences for regulatory wiggle room exploitation. Transient investors have a short horizon and are focused on achieving short-term trading profits. For them the considerations of *Hypothesis 1 - Transparency* apply, as they will presumably benefit from the additional transparency that holding cautious firms provides. Quasi-indexers have a long-term perspective and follow a diversified and passive investment approach. Since their discretion in selecting stocks is limited, I expect them to have the weakest preferences for wiggle room and thus use them as the benchmark category for the following analyses. Dedicated investors also have a long-term horizon, but their strategy is consistent with a "relationship investing" role, as they provide stable capital to a small number of firms (Bushee, 2001, p.214). The preferences of dedicated investors could either be geared towards more aggressive and thus less transparent firms, consistent with *Hypothesis 1 - Transparency*, or inclined towards the more cautious firms with allegedly more trustworthy management. This could occur because the managers of cautious firms are considered honest by the employees, which is crucial for a relationship based on trust to develop (O'Neill, 2002). Such a relationship is likely to increase employee satisfaction (Dirks and Ferrin, 2002), which in turn generates long-term value (Edmans, 2011). Additionally, trustworthy managers are particularly important when one follows a strategy of relationship investing, as is the case for dedicated investors. Therefore, I expect them to prefer cautious firms (*Hypothesis 3 - Trust*).

I test these hypotheses in models (3) and (4) of Table 5, where exploited PWR is regressed on a dummy for investor strategy using quasi-indexers as benchmark. The average exploited PWR of the benchmark is 39.3%. The coefficients show that transient investors tend to hold firms that exploit 1% less regulatory wiggle room than quasi-indexers ($\frac{-0.248}{39.3}$), confirming *Hypothesis 1 - Transparency*. Also, the findings support *Hypothesis 3 - Trust*, as the exploited PWR of dedicated investors is on average 5% smaller than that of quasi-indexers ($\frac{-1.847}{39.3}$).

To corroborate the claim that only the preferences of transient investors are motivated by differences in trading activity, I control for both portfolio turnover and investment horizon. The coefficient of the transient investors becomes insignificant, which indicates that the driver behind the observed relationship is linked with trading behavior. The coefficient of the dedicated investors remains unchanged and highly significant. This points towards the importance of the "relationship investing" channel: Instead of preferring the less transparent firms and profit from their long investment horizon to gain an informational advantage, these investors prefer firms that are more cautious and trustworthy.

- Table 5 -

3.3 Financial adviser misconduct and changes in PWR

If an investor who values trust prefers cautious firms because they appear more trustworthy, then a change in the perceived importance of trust should also induce a change in the revealed preferences for regulatory wiggle room exploitation. To test whether this is the case, I use the disclosure of financial adviser misconduct (Egan et al., 2019; Egan, Matvos, and Seru, 2018) as a quasi-exogenous shock to investors' preferences. The relationship between an institutional investor and her financial advisers is based on trust: The latter plays the role of a "money doctor" who is not only employed, but also *trusted* by the investor who seeks advice on how to best make risky investment decisions (Gennaioli et al., 2015, p. 92). When this trust is breached, its importance will become salient and the exposed investor will be more cautious in choosing the right advisers (Gurun et al., 2017). If *Hypothesis 3 - Trust* holds, investors for whom trust is important will also exhibit low PWR. But then a shock to the perceived importance of trust will translate into a change in PWR. I posit that the exposure to financial misconduct can be seen as such a shock and expect it to cause a decrease in PWR, after controlling for a change that occurs at a similar investor who does not experience misconduct. The effect ought to be strongest following disclosures that lead to the firing of the financial adviser, as such reaction suggests that the disclosure did indeed represent a breach of the investor's trust.

The validity of the identification strategy would be threatened if unaffected institutional investors would themselves impose stricter internal controls as a consequence of seeing competitors punishing misconduct. However, this seems unlikely since the financial consequences for the affected firm are usually mild. The median amount for which the misconduct cases are settled lies at USD 40,000 (Egan et al., 2019, p. 11), i.e., 0.01% of the assets the median investor manages. Moreover, institutional investors employ on average over 150 different advisers. Even if a competitor becomes informed of the ongoing misconduct investigation, it is likely that it will appear to her as an isolated case that does not warrant a change in her own organization. Another concern is that some institutional investors may find out about the adviser's misconduct before it is disclosed and that they would already have reacted by the time the malpractice was public. However, this should bias against finding a significant effect.

Empirical framework - Estimation of treatment effects

To assess the consequences of misconduct I focus on the sub-sample of institutional investors that employ advisers that are registered with the Financial Industry Regulatory Authority (FINRA). FINRA requires for all registered financial advisers to report their entire employment and disclosure histories, including all customer disputes and disciplinary events. These reports are then made publicly available, and were used by Egan et al. (2019) to construct a panel of yearly adviser observations that contains both their current employer and their track record of regulatory disclosures.[5] I collapse this panel at the employing firm level to obtain a measure of how many misconduct disclosures a given firm experiences over a year. I then manually match all firms in this data set with Thomson 13F and keep only the matching institutions. This results in over 18,000 yearly observations of 2,500 institutional investors over the period from 2007 to 2015. Appendix Table A2 shows that there are only minor differences between the full and matched samples: Compared to the full sample, the average investor in the matched sample has an investment horizon that is 0.5 quarters longer, a turnover that is 2 percentage points smaller, and 7% fewer assets under management. Also, investment advisers make up a larger part of the matched sample (92%) than of the full sample (79%).

I define the treatment group as all institutional investors who employ financial advisers who disclose misconduct cases during a given year. I differentiate between three types of treatment: "All", which covers investors who experience between 1 and 10 disclosures of any kind during a given year, "Criminal", which covers only disclosures of criminal charges, and "Fired", which covers only disclosures that lead to the termination of the employment relation between adviser and investor. This yields respectively a total of 323, 81, and 139 treatment observations. Appendix Figure A1 plots the total number of advisers employed by year together with the fraction that reports misconduct. While there is a steady increase in the total number of advisers employed, the fraction that reports a misconduct event during a given year remains largely constant. To assess the magnitude of the treatment effect, I compute the total change of PWR during a year, ΔPWR_T, and retain only one observation for each investor-year.

Since treatment assignment is unlikely to be random, I construct a control group relying

[5] I am very grateful to Mark Egan, Gregor Matvos, and Amit Seru for sharing the data with me. Additional information can be found at `eganmatvosseru.com`.

on nearest neighbor propensity score matching (Rosenbaum and Rubin, 1983). This ought to ensure that the treatment and control groups are statistically indistinguishable along observables. To achieve this, I control for investor characteristics observed during the last quarter (or year) before treatment occurs. Specifically I account for the #Advisers that are employed by a given investor, the average qualification exams passed by them, ∅Exam_63, ∅Exam_65, and ∅Exam_66, their average years of experience as advisers, ∅Experience, and whether the firm employs investors that were fired in the past due to a misconduct allegation. I also control for several variables that account for differences in investment strategies and that are potentially correlated with the outcome of interest: Portfolio turnover and duration, exposure to the FF-3 factor portfolios, an indicator for investors who experienced a loss in the previous quarter, the logarithm of assets under management, and of the number of portfolio firms. Appendix Table A3 shows logit regressions of treatment assignment on investor characteristics. The coefficients have the expected signs, and the most sizable impact on the probability of being treated is attributable to employing advisers that were previously fired as a consequence of misconduct. This is in line with findings in Egan et al. (2019) and also with Dimmock, Gerken, and Graham (2018) who show that financial advisers who engaged in fraudulent behavior will also influence their future co-workers towards malpractice.

Appendix Table A4 reports the means of the covariates in the treatment and control samples, together with a test for differences. While the two groups are not perfectly balanced for the "Any" treatment, they are for the "Fired" treatment, which also represents the main case of interest. Propensity score estimates are constructed following Abadie and Imbens (2006, 2016) and standard errors are adjusted to account for the fact that the scores themselves are estimates and not observed. Finally, to compute the average treatment effects on the variable of interest, ΔPWR_T, I match treated and control investors following the nearest neighbor technique. In unreported analyses, I use an alternative estimation strategy for the propensity score proposed by Imbens and Rubin (2015). This methodology leads to the inclusion of 8 linear covariates and 19 interaction terms. The results remain robust to this specification, and the overlap is not overly improved.

Main findings - Financial adviser misconduct and changes in PWR

Table 6 shows the effect of the different treatment types on exploited portfolio wiggle room. In model (1) I consider all misconduct disclosures. Here the effect on PWR is negative but insignificant. This may be because I do not distinguish between different treatment intensities: A minor misconduct case that is settled for a few thousand dollars is unlikely to generate any serious consequence. The coefficients in models (2) and (3) are both negative and significant. For example, being exposed to a misconduct allegation which leads to the firing of the culprit is related to a reduction in PWR of over 4 percentage points over the treatment year. This is an economically sizeable effect, representing 0.52 standard deviations of ΔPWR_T. In models (4) to (6), I examine whether this effect is observable before treatment and if it vanishes afterward. First, there is no significant change in PWR in the one year prior. This suggests that investors do not react to malpractices before the allegations are publicly disclosed. The coefficient in the year after treatment is somewhat smaller but still negative and significant. Two years after treatment, the effect is not significant anymore but the coefficient remains negative. This suggests that it is likely that the observed effects are not only a short-lived overreaction to the increased salience of fraud (Bondt and Thaler, 1985), but rather that they represent a persistent shift in investors' preferences.

- Table 6 -

Figure 2 further explores how the effect evolves through time by depicting the estimated average treatment effect from three periods before to three periods after the misconduct allegations are disclosed. Panel 2a confirms that there is no significant change in PWR when one does not differentiate between the seriousness of the misconduct cases. Panel 2b provides additional evidence that when one considers only disclosures that lead to the firing of the adviser, the PWR of the treated institutional investor significantly decreases and that this decrease is persistent. Additionally, the fact that there are no observable effects before treatment points out that institutional investors usually do not anticipate the misconduct disclosures.

- Figure 2 -

Drivers of changes in PWR following financial adviser misconduct

What are the main drivers behind the observed decrease in PWR? In general, the portfolio wiggle room of an institutional investor decreases when she (i) buys firms that are more cautious or (ii) sells firms that are more aggressive than the firms she currently holds, or (iii) when the firms she holds become themselves more cautious. To see whether this is the case I construct portfolios consisting of those shares that an investor buys, sells, and does not trade during a quarter. For each of these portfolios, I then compute the portfolio wiggle room: PWR^{buys}, for the shares, bought, PWR^{init}, for the initiating trades, PWR^{sells}, for the shares sold, and PWR^{exit} for the stocks exited during a quarter. The obtain the outcome variables of interest, I subtract from all these measures the initial PWR of the investor and sum up the available quarters over a year. Finally, I compute the change in the aggressiveness of portfolio firms by keeping the holdings constant but looking at the lagged wiggle room of the firms. $\Delta\text{PWR}^{noTrade}$ is then the % difference between the investor's current PWR and the PWR she would have had the previous quarter if she did not rebalance her holdings.

In Table 7 I estimate the average treatment effect that experiencing financial adviser misconduct has on these measures. I report only the coefficient for the main treatment of interest, namely the one that causes the financial adviser to be fired. The first model presents the total change in PWR for the year of treatment. The coefficient in model (2) is negative and significant: Treated investor tend to buy shares of firms that are more cautious than the ones they currently hold in their portfolios. The insignificant coefficient of the initiating trades portfolio in model (3) suggests that investors do not buy stakes in cautious firms they do not already hold in their portfolios. Instead they seem to allocate more capital to existing cautious holdings. While the coefficient in model (4) is insignificant, model (5) shows that treated investor tend to exit firms that are more aggressive than the ones they currently hold in their portfolios. Finally, the coefficient of $\Delta \text{PWR}_T^{noTrade}$ is negative and significant. This implies that the trading activity of investors is not the only driver behind the observed changes in PWR. What also matters is the change in firms' behavior with respect to regulatory wiggle room exploitation: The firms that are held by the treated investors become more cautious during the treatment year.

- Table 7 -

Taken together these findings provide further evidence that supports *Hypothesis 3 - Trust* and highlight the important consequences of breaking the investor's trust (Lins et al., 2017). When the perceived value of being honest and trustworthy increases investors will prefer firms that are more cautious and that do not excessively take advantage of the regulatory environment.

4 Wiggle Room preferences and firm behavior

This section explores the relationship between the preferences of institutional investors and portfolio firms. In other words, we now change the focus of the analysis and run tests at the *firm-level.* To obtain exogeneous variation in institutional ownership we look at instances of mergers between institutional investors as discussed in Lewellen and Lowry (2021).[6]

- Table 8 -

We start by constructing the firm-level measure of investors' preferences, proxied with a weighted average of PWR for every firm in our sample. In Table 8 we start by running regressions of firms' exploited wiggle room (WR_Firm) on this measure of institutional investors'

[6] Another approach commonly used in the literature is the reconstitution of Russel1000/2000 indexes. This is not appealing in this setting, as the changes in institutional ownership around this experiment stem from passive owners that are unlikely to have a strong impact of firms' policies

preferences (1) and firm-level controls (2). We find a strong correlation between these two measures, which holds after controlling for the average duration of a firm's shareholders, its total institutional ownership and number of institutional investors, as well as firm's market capitalization.

We control for selection bias in the last two columns of Table 8. To achieve this, we start by restricting the sample of investors to those that are either a blockholder, defined as holding a share of at least 5%, or being among the five largest owners of a firm. Second, we look at only those investors that were a target of an acquisition and record the PWR preferences of the *acquiring* institution as the measure of exogenous PWR preferences.[7] The main dependent variable is constructed as the absolute difference between the firm's exploited WR in the quarter before the acquisition and the preferences of the acquiring institution.

Models (3) and (4) show that after an acquisition takes place between two institutional investors, the firm modifies its exploited wiggle room to cater to the preferences of its new owner. In the eight quarters after such an event, the difference between the firm's WR and the acquirer's PWR decreases by 1.3 percentage points, or 21% of a standard deviation.

The evidence presented in this section suggests that the preferences of institutional investors indeed influence the behavior of companies with respect to the exploitation of the regulatory environment.

5 Performance and risk implications of PWR

As it turns out that institutional investors differ significantly with respect to their preferences for wiggle room exploitation, I now address the third question of this paper, namely whether having such preferences affects portfolio performance and exposure to idiosyncratic risk. Figure 3 depicts the main findings of this section, namely a negative relationship between PWR and portfolio alpha and a positive one between PWR and exposure to idiosyncratic

[7] In untabulated results we confirm that our results are robust to running these tests with the full sample of institutional investors.

risk.

- Figure 3

5.1 Excess returns and portfolio alphas

As it turns out that institutional investors differ significantly with respect to their preferences for wiggle room exploitation, I now address the second question of this paper, namely whether having such preferences affects portfolio performance and exposure to idiosyncratic risk. Figure 3 depicts the main findings of this section, namely a negative relationship between PWR and portfolio alpha and a positive one between PWR and exposure to idiosyncratic risk.

I test this hypothesis in Table 9, where in model (1) excess returns are regressed on PWR, the full set of controls from the previous tables, and investors' exposure to the 3 factor Fama-French portfolios. Model (2) also accounts for differences in investment horizon and portfolio turnover, and model (3) includes instead general investment strategy. In columns (4) to (6), I perform the same analyses using portfolio alpha as dependent variable. The coefficients on the first three models are negative but insignificant, which indicates that there is no meaningful relationship between preferences for wiggle room exploitation and excess returns. However, the coefficients of the last three models are all negative and significant contradicting *Hypothesis 4 - Performance*: A one standard deviation increase in PWR implies a decrease in alpha of 0.2% or 0.08 standard deviations. Appendix Table A5 confirms these findings when controlling for exposure to the returns on the FF 5-factor portfolios. There seemingly is a negative relationship between preferences for wiggle room exploitation and portfolio performance: When an investor holds aggressive firms, she tends to generate smaller portfolio alphas.

- Table 9 -

5.2 Exposure to idiosyncratic risk

Firms that fully exploit regulatory wiggle room could have more opportunities available to conceal poor performance and smooth earnings. Aggressive firms could avoid a short-lived negative price impact on the stock price by barely beating analysts' forecasts (Bhojraj et al., 2009). Moreover, the literature has shown that firms manage earnings in order to reduce fluctuations in reported net income (Trueman and Titman, 1988, p. 127). Therefore, it could be the case that an investor who has a preference for aggressive firms will generate quarterly returns that are less volatile. I expect to see a negative relationship between PWR and measures for portfolio risk (*Hypothesis 5 - Risk*).

I test this in Table 10, where I regress the exposure to idiosyncratic risk of investors' returns on PWR and the set of controls from the previous tables. The results confirm *Hypothesis 5 - Risk*: Model (1) shows that a one standard deviation increase in PWR is associated with a decrease in idiosyncratic risk exposure of 13% of a standard deviation ($\frac{0.05*0.05}{0.02}$). Model (2) shows that this relationship is robust to controlling for the volatility of PWR. To see whether this association is caused by differences in investment horizon, portfolio turnover, or general strategy, I sequentially control for these characteristics in models (3) and (4) and find the same association within a specific investor group. Finally, Appendix Table A6 confirms that these relationships continue to hold when risk measures are computed by taking the exposures to the 5-factor FF portfolios into account.

Taken together, the findings point towards a negative correlation between PWR and portfolio risk: Having a preference towards holding firms that exploit regulatory wiggle room does decrease portfolio alphas but reduces exposure to idiosyncratic risk.

- Table 10 -

6 Further analyses

In this section, I perform additional analyses and robustness tests. First, I explore whether the relationship between investors' preferences for regulatory wiggle exploitation and portfolio performance is due to a single proxy or rather due to the common factor captured by the PWR measure. Then I ask if market factors correlate with the preferences of institutional investors in a way that is consistent with my hypotheses.

6.1 Portfolio performance and individual wiggle room proxies

It could be the case that the relationship between exploiting regulatory wiggle room and portfolio performance is driven by a single proxy instead of capturing the effect of their common component. For instance, the positive correlation between PWR and the volatility of portfolio returns could be exclusively attributable to the effects of earnings management (Trueman and Titman, 1988). I test this in Table A7, where I regress the measures of portfolio performance and risk on the complete set of proxies for exploited wiggle room.

Models (1) and (2) indicate that, with the exception of #Tax havens, all coefficients of the individual proxies are insignificant when excess returns are used as the dependent variable. This is in line with the insignificant relationship between excess returns and PWR found in Appendix Table 9. Models (3) and (4) depict a more nuanced relationship between the individual WR components and portfolio alpha. A portfolio that consists of firms that exploit tax credits more aggressively, and thus have smaller long-term tax rates, tends to generate higher alphas. This is consistent with evidence that some institutional investors actively engage with portfolio firms to make them plan taxes more efficiently and exploit the available tax credits (Cheng, Huang, Li, and Stanfield, 2012, p. 1494). The coefficient of DTAX is insignificant but also positive. The number of subsidiaries in tax haven countries that the firm has is associated with lower portfolio alphas: A one standard deviation increase in #Tax havens relates to a decrease in portfolio alpha of 7.9 standard deviations ($\frac{-0.03*5.23}{0.02}$).

This is consistent with managers effectively using tax havens to derive private benefits to the detriment of noncontrolling shareholders (Bennedsen and Zeume, 2018, p. 1222). All other proxies have negative but insignificant coefficients.

In Appendix Table A8 I perform the same analysis but controlling for exposure to the FF-5 portfolios (Fama and French, 2015). Models (1) and (2) confirm the previous results as all coefficients of interest are insignificant. Models (3) and (4) are also mainly in line with the previous findings. In addition to those, the negative coefficient of DQ becomes significant at the 5% level: A one standard deviation increase in the disaggregation quality is associated with a decrease in portfolio alpha of 3.7% of a standard deviation ($\frac{-0.01*0.11}{0.03}$). This is in line with evidence suggesting that managers avoid revealing information of poorly performing business segments via aggregation of financial statements (Berger and Hann, 2007, p. 871). The coefficient of earnings management becomes positive and significant: A one standard deviation increase in EM is associated with an increase in portfolio alpha of 8.8% of a standard deviation ($\frac{0.012*0.22}{0.03}$). This is consistent with the potentially positive effects of earnings management on firm value, for instance by helping firms to maintain a high stock valuation (Shleifer, 2004, p. 416).

In models (5) and (6) of Appendix Table A7, I study the relationship between portfolio risk and the individual WR proxies. The coefficients of DQ, Just beat, and #Tax havens are all negative and highly significant which is in line with the overall effect of portfolio wiggle room. Holding firms that report financial statement parsimoniously, barely beat analysts' forecasts, and have several subsidiaries in tax haven countries tends to decrease the volatility of portfolio returns and the exposure to idiosyncratic risk.

The coefficients of CashETR and EM are also highly significant but positive. This suggests that holding firms that manage earnings more and pay relatively fewer taxes is correlated with larger exposure to idiosyncratic risk. This is consistent with the evidence on big bath accounting, i.e., when managers prefer frequent small gains and rare large losses to more frequent, albeit smaller losses (Burgstahler and Dichev, 1997). In models (5) and

(6) of Appendix Table A8 I also control for the exposure to the FF-5 factor portfolios. The magnitude of the coefficients remains similar and their signs do not change.

Taken together, these findings highlight the relative importance of the individual proxies for exploiting regulatory wiggle room. Moreover, it seems that the relationship one observes when analyzing the joint effect of portfolio wiggle room cannot be subsumed by only looking at a subset of these proxies.

6.2 Sentiment, market uncertainty, and preferences for PWR

Previous literature argues that changes in market sentiment that occur over time affect stock prices in a heterogeneous manner, as sentiment-based demand shocks vary across firms. Due to both the trading of irrational investors who temporarily emphasize growth over profitability, and to market frictions that impose limits on arbitrageurs, the demand for "more speculative securities" will increase. Such securities are broadly characterized by being difficult to value objectively (Baker and Wurgler, 2007, pp. 131-132). If *Hypothesis 1 - Transparency* holds, firms that exploit more regulatory wiggle room are also less transparent which in turn makes them more speculative. If the institutional investors themselves are subject to the effects of sentiment either directly or indirectly (through limits of arbitrage or the preferences of their customers), I expect to find a positive relationship between market sentiment and PWR. I also expect the strength of this relationship to vary across investor types: For short-term, high turnover, and transient investors market sentiment will play less of a role compared to the respective benchmarks. This could possibly be due to the fact that those types of investors are closer in nature to arbitrageurs that would profit from mispricings rather than modify their holdings.

To test this, I download the monthly orthogonalized market sentiment index from Jeffrey Wurgler's website and compute the average for each quarter (Baker and Wurgler, 2006). I then interact this with dummies for institutional investor type, namely investment horizon, portfolio turnover, and general strategy. I regress exploited PWR on these variables and the full set of controls in Table A9. In all models I find a positive and highly significant relationship between PWR and investor sentiment: Regardless of the benchmark category, a one standard deviation increase in sentiment is associated with an increase in exploited PWR of 11.5% of a standard deviation ($\frac{0.009*0.64}{0.05}$). When sentiment is interacted with horizon, I find a negative additional effect on short-term investor: Having a short average portfolio duration more than halves the impact of sentiment on PWR, which hints that short-term investors tend to be less affected by upsprings in market sentiment. In model (2) I also find a negative, albeit smaller, coefficient on the interaction between sentiment and high turnover, which is in line with the previous point. In model (3) it seems that there is no additional effect of a given general strategy. However, none of these effects is large enough to reverse the overall positive correlation between market sentiment and exploited PWR, which confirms *Hypothesis 1 - Transparency*.

It could be that due to their structural characteristics some institutional investors will react slowly to changes in market sentiment. In Table A10 I explore this by using as explanatory variable the average sentiment of the previous quarter. The results remain mostly unchanged, but the interaction coefficient of low turnover becomes significant at the 10% confidence level. This suggests that these investors are indeed more affected by sentiment, but require more time to rebalance their holdings.

An additional channel through which market factors relate to investors' preferences for wiggle room exploitation could be the degree of market uncertainty: When it surpasses a critical threshold, investors may be forced to liquidate their assets in fire sales (Shleifer and Vishny, 2011) causing a "flight to quality within the stock market" (Baker and Wurgler, 2007, p.133). If *Hypothesis 3 - Trust* holds, I expect institutional investors to prefer holding firms that are more cautious when market uncertainty is very high. This is because these firms may have accumulated more credibility (Eugster and Wagner, 2018) which could be particularly valuable in times of high uncertainty (Lins et al., 2017).

To test this I download the monthly time-series of the CBOE Volatility Index (VIX) and compute the average over a given quarter. I identify periods of high uncertainty by including VIX squared as an additional explanatory variable. Models (4) to (6) of Table A9 show regressions of PWR on these variables and the complete set of controls. The coefficient on the average VIX level suggests that during normal times there is a positive relationship between preferences for wiggle room exploitation and market uncertainty: A one standard deviation (7.7) increase in VIX is related to an increase in PWR of 34.3% of a standard deviation ($\simeq \frac{7.7}{0.05} * (0.003 - 2 * 7.7 * 4.5 * 10^{-5})$). However, when market volatility surpasses a critical point, this relationship is reversed: When the VIX is larger than 33 ($\simeq \frac{0.003}{2*4.5*10^{-5}}$), any further increase will be related to a smaller PWR.[8] This finding supports *Hypothesis 3 - Trust*, as investors seem to prefer more cautious firms when market conditions are uncertain, suggesting that being trustworthy is particularly valuable during turbulent times.

In untabulated analyses, I explore the interaction effect between market uncertainty and the investor type. I find that when an investor has a short-term horizon or a high portfolio turnover the effect of market uncertainty will become smaller. For investors with low turnover, the impact of the VIX will be magnified. This is again consistent with the idea of frequent traders being somewhat less subject to the influences of market conditions.

7 Conclusion

In the first part of this paper, I analyze the holdings of institutional investors through a novel perspective: The inclination towards holding firms that exploit more or less of the available regulatory wiggle room. I ask whether some investors are concerned about additional aspects other than performance, namely whether it matters to them *how results are achieved* and uncover substantial heterogeneity amongst investor types. Short-term investors, frequent traders, and dedicated institutions hold firms that are more cautious towards exploiting the available regulatory wiggle room. This could be related to the additional transparency and trustworthiness of cautious firms. In support of this I find that when market sentiment

[8] During the height of the financial crises, the VIX surpassed 80.

increases and investors usually prefer more opaque firms, they also tend to prefer firms that aggressively exploit the regulatory wiggle room.

There seems to be a link between the perceived value of trust and investors' preferences for WR. When an investor fires a financial adviser following the disclosure of misconduct, she will thereafter significantly reduce her portfolio wiggle room compared to a similar investor whose trust was not breached. This reduction is economically significant and is not reversed in the three following years. Moreover, it seems to be driven by both portfolio rebalancing activities and by changes that occur at the level of the portfolio firms. Hence, a plausibly exogenous shock to an investor's preferences leads her to change the aggressiveness with which her portfolio firms exploit the regulatory environment.

Not only do the preferences of institutional investors matter for their asset allocation choices, but these preferences also impact firm behavior. After a merger between two institutional investors, the firms where the target was a blockholder or large investors change their Wiggle Room to cater to the preferences of the acquiring investor.

In the last part, I ask whether having such preferences impacts investors' performance. It seems that holding firms that fully exploit wiggle room does generate somewhat smaller portfolio alphas after controlling for exposures to the FF-3 or FF-5 factor portfolios. However, holding such firms significantly reduces exposure to idiosyncratic risk. This could be related to aggressive firms using regulatory wiggle room to smoothen their performance. I also examine the relative importance of the individual proxies and cannot attribute the established relationship to any single one of them.

Overall, this paper documents the presence of a heterogeneity in investors' preferences for the exploitation of regulatory wiggle room which cannot be fully explained by differences in risk-return profiles. It then shows how a change in investors' preferences can have a substantial impact on their investment decisions. This finding is of interest as it identifies a further channel through which firms that refrain from exploiting regulation could be rewarded, namely by better access to capital from investors who value trust highly.

References

Abadie, A., Imbens, G. W., 2006. Large Sample Properties of Matching Estimators for Average Treatment Effects. Econometrica 74, 235–267.

Abadie, A., Imbens, G. W., 2016. Matching on the Estimated Propensity Score. Econometrica 84, 781–807.

Amiraslani, H., Lins, K. V., Servaes, H., Tamayo, A., 2017. A matter of Trust? The bond market benefits of corporate social capital during the financial crisis. Working paper .

Ang, A., Hodrick, R. J., Xing, Y., Zhang, X., 2006. The Cross-Section of Volatility and Expected Returns. The Journal of Finance 61, 259–299.

Baker, M., Wurgler, J., 2006. Investor Sentiment and the Cross-Section of Stock Returns. The Journal of Finance 61, 1645–1680.

Baker, M., Wurgler, J., 2007. Investor Sentiment in the Stock Market. Journal of Economic Perspectives 21, 129–151.

Bennedsen, M., Zeume, S., 2018. Corporate Tax Havens and Transparency. Review of Financial Studies 31, 1221–1264.

Berger, P. G., Hann, R. N., 2007. Segment Profitability and the Proprietary and Agency Costs of Disclosure. The Accounting Review 82, 869–906.

Bhojraj, S., Hribar, P., Picconi, M., McInnis, J., 2009. Making Sense of Cents: An Examination of Firms That Marginally Miss or Beat Analyst Forecasts. The Journal of Finance 64, 2361–2388.

Biggerstaff, L., Cicero, D. C., Puckett, A., 2015. Suspect CEOs, unethical culture, and corporate misbehavior. Journal of Financial Economics 117, 98–121.

Bird, A., Karolyi, S. A., 2017. Governance and Taxes: Evidence from Regression Discontinuity. The Accounting Review 92, 29–50.

Bondt, W. F. M. D., Thaler, R., 1985. Does the Stock Market Overreact? The Journal of Finance 40, 793.

Boone, A. L., White, J. T., 2015. The effect of institutional ownership on firm transparency and information production. Journal of Financial Economics 117, 508–533.

Burgstahler, D., Dichev, I., 1997. Earnings management to avoid earnings decreases and losses. Journal of Accounting and Economics 24, 99–126.

Bushee, B. J., 1998. The influence of institutional investors in myopic R&D investment behavior. The Accounting Review 73, 305.

Bushee, B. J., 2001. Do Institutional Investors Prefer Near-Term Earnings over Long-Run Value? Contemporary Accounting Research 18, 207–246.

Cameron, A. C., Gelbach, J. B., Miller, D. L., 2011. Robust Inference With Multiway Clustering. Journal of Business & Economic Statistics 29, 238–249.

Carhart, M. M., 1997. On Persistence in Mutual Fund Performance. The Journal of Finance 52, 57–82.

Chen, S., Miao, B. I., Shelvin, T., 2015. A New Measure of Disclosure Quality: The Level of Disaggregation of Accounting Data in Annual Reports. Journal of Accounting Research 53, 1017–1054.

Chen, X., Harford, J., Li, K., 2007. Monitoring: Which institutions matter? Journal of Financial Economics 86, 279–305.

Cheng, C. S. A., Huang, H. H., Li, Y., Stanfield, J., 2012. The Effect of Hedge Fund Activism on Corporate Tax Avoidance. The Accounting Review 87, 1493–1526.

Cline, B. N., Walkling, R. A., Yore, A. S., 2018. The consequences of managerial indiscretions: Sex, lies, and firm value. Journal of Financial Economics 127, 389–415.

Cremers, M., Pareek, A., 2015. Short-Term Trading and Stock Return Anomalies: Momentum, Reversal, and Share Issuance. Review of Finance 19, 1649–1701.

Dechow, P., Ge, W., Schrand, C., 2010. Understanding earnings quality: A review of the proxies, their determinants and their consequences. Journal of Accounting and Economics 50, 344–401.

Dechow, P. M., Sloan, R. G., Sweeney, A. P., 1995. Detecting Earnings Management. The Accounting Review 70, 193–225.

Del Guercio, D., 1996. The distorting effect of the prudent-man laws on institutional equity investments. Journal of Financial Economics 40, 31–62.

Diamond, D. W., Verrecchia, R. E., 1991. Disclosure, Liquidity, and the Cost of Capital. The Journal of Finance 46, 1325–1359.

Dimmock, S. G., Gerken, W. C., Graham, N. P., 2018. Is Fraud Contagious? Coworker Influence on Misconduct by Financial Advisors. The Journal of Finance 73, 1417–1450.

Dirks, K. T., Ferrin, D. L., 2002. Trust in leadership: Meta-analytic findings and implications for research and practice. Journal of Applied Psychology 87, 611–628.

Dyck, I. J. A., Lins, K. V., Roth, L., Wagner, H. F., 2018. Do Institutional Investors Drive Corporate Social Responsibility? International Evidence. Journal of Financial Economics Forthcoming.

Dyreng, S., Lindsey, B. P., 2009. Using Financial Accounting Data to Examine the Effect of Foreign Operations Located in Tax Havens and Other Countries on US Multinational Firms' Tax Rates. Journal of Accounting Research 47, 1283–1316.

Dyreng, S. D., Hanlon, M., Maydew, E. L., 2008. Long-Run Corporate Tax Avoidance. The Accounting Review 83, 61–82.

Edmans, A., 2011. Does the stock market fully value intangibles? Employee satisfaction and equity prices. Journal of Financial Economics 101, 621–640.

Edmans, A., Manso, G., 2011. Governance Through Trading and Intervention: A Theory of Multiple Blockholders. Review of Financial Studies 24, 2395–2428.

Egan, M., Matvos, G., Seru, A., 2019. The Market for Financial Adviser Misconduct. Journal of Political Economy 127, 233–295.

Egan, M. L., Matvos, G., Seru, A., 2018. When Harry fired Sally: The double standard in punishing misconduct. Working paper .

Eugster, F., Wagner, A. F., 2018. Earning Investor Trust: The Role of Past Earnings Management. Working paper .

Fama, E. F., French, K. R., 1996. Multifactor Explanations of Asset Pricing Anomalies. The Journal of Finance 51, 55–84.

Fama, E. F., French, K. R., 2015. A five-factor asset pricing model. Journal of Financial Economics 116, 1–22.

Fink, L., 2018. A Sense of Purpose - BlackRock's annual letter to CEOs. https://www.blackrock.com/corporate/en-de/investor-relations/larry-fink-ceo-letter .

Frank, M. M., Lynch, L. J., Rego, S. O., 2009. Tax Reporting Aggressiveness and Its Relation to Aggressive Financial Reporting. The Accounting Review 84, 467–496.

Fudenberg, D., Tirole, J., 1995. A Theory of Income and Dividend Smoothing Based on Incumbency Rents. Journal of Political Economy 103, 75–93.

Gennaioli, N., Shleifer, A., Visgny, R., 2015. Money Doctors. The Journal of Finance 70, 91–114.

Gibson, R., Krueger, P., Mitali, S. F., 2021. The Sustainability Footprint of Institutional Investors: ESG Driven Price Pressure and Performance. Working paper .

Gibson, R., Sohn, M., Tanner, C., Wagner, A. F., 2017. Investing in Managerial Honesty. Working paper .

Gurun, U. G., Stoffman, N., Yonker, S. E., 2017. Trust Busting: The Effect of Fraud on Investor Behavior. Review of Financial Studies .

Hanlon, M., Heitzman, S., 2010. A review of tax research. Journal of Accounting and Economics 50, 127–178.

Hong, H., Kacperczyk, M., 2009. The price of sin: The effects of social norms on markets. Journal of Financial Economics 93, 15–36.

Hong, H., Kostovetsky, L., 2012. Red and blue investing: Values and finance. Journal of Financial Economics 103, 1–19.

Hwang, C.-Y., Titman, S., Wang, Y., 2017. Investor Tastes, Corporate Behavior and Stock Returns: An Analysis of Corporate Social Responsibility. Working paper .

Imbens, G., Rubin, D. B. (eds.), 2015. Casual inference for statistics, social, and biomedical sciences: An introduction / Guido W. Imbens, Donald B. Rubin. Cambridge University Press, New York, NY.

Jones, J. J., 1991. Earnings Management During Import Relief Investigations. Journal of Accounting Research 29, 193.

Kacperczyk, M., Sialm, C., Zheng, L., 2008. Unobserved Actions of Mutual Funds. Review of Financial Studies 21, 2379–2416.

Ke, B. I., Petroni, K. R., Yu, Y., 2008. The Effect of Regulation FD on Transient Institutional Investors' Trading Behavior. Journal of Accounting Research 46, 853–883.

Kothari, S. P., Leone, A. J., Wasley, C. E., 2005. Performance matched discretionary accrual measures. Journal of Accounting and Economics 39, 163–197.

Lewellen, K., Lowry, M. B., 2021. Does Common Ownership Really Increase Firm Coordination? Journal of Financial Economics Forthcoming.

Lins, K. V., Servaes, H., Tamayo, A. N., 2017. Social Capital, Trust, and Firm Performance: The Value of Corporate Social Responsibility during the Financial Crisis. The Journal of Finance 72, 1785–1824.

O'Donovan, J., Wagner, H. F., Zeume, S., 2018. The Value of Offshore Secrets – Evidence from the Panama Papers. Working paper .

O'Neill, O., 2002. A question of trust: The BBC Reith Lectures 2002. Cambridge University Press.

Payne, J. L., Thomas, W. B., 2003. The Implications of Using Stock–Split Adjusted I/B/E/S Data in Empirical Research. The Accounting Review 78, 1049–1067.

Rosenbaum, P. R., Rubin, D. B., 1983. The central role of the propensity score in observational studies for causal effects. Biometrika 70, 41–55.

Rountree, B., Weston, J., Allayanis, G., 2008. Do investors value smooth performance? Journal of Financial Economics 90, 237–251.

Seasholes, M. S., Zhu, N., 2010. Individual Investors and Local Bias. The Journal of Finance 65, 1987–2010.

Shleifer, A., 2004. Does Competition Destroy Ethical Behavior? The American Economic Review 94, 414–418.

Shleifer, A., Vishny, R., 2011. Fire Sales in Finance and Macroeconomics. Journal of Economic Perspectives 25, 29–48.

Trueman, B., Titman, S., 1988. An Explanation for Accounting Income Smoothing. Journal of Accounting Research 26, 127.

Wagner, A. F., Zeckhauser, R. J., Ziegler, A., 2018. Company stock price reactions to the 2016 election shock: Trump, taxes, and trade. Journal of Financial Economics 130, 428–451.

Figures

Figure 1: Time series of mean exploited WR on the firm- and investor-level
The figure depicts the time series evolution of the mean exploited WR across all institutional investors (PWR_mean) and the mean exploited WR across all Compustat firms (WR_mean). Both variables are winsorized at the 5% level. All variables are described in in Table 1.

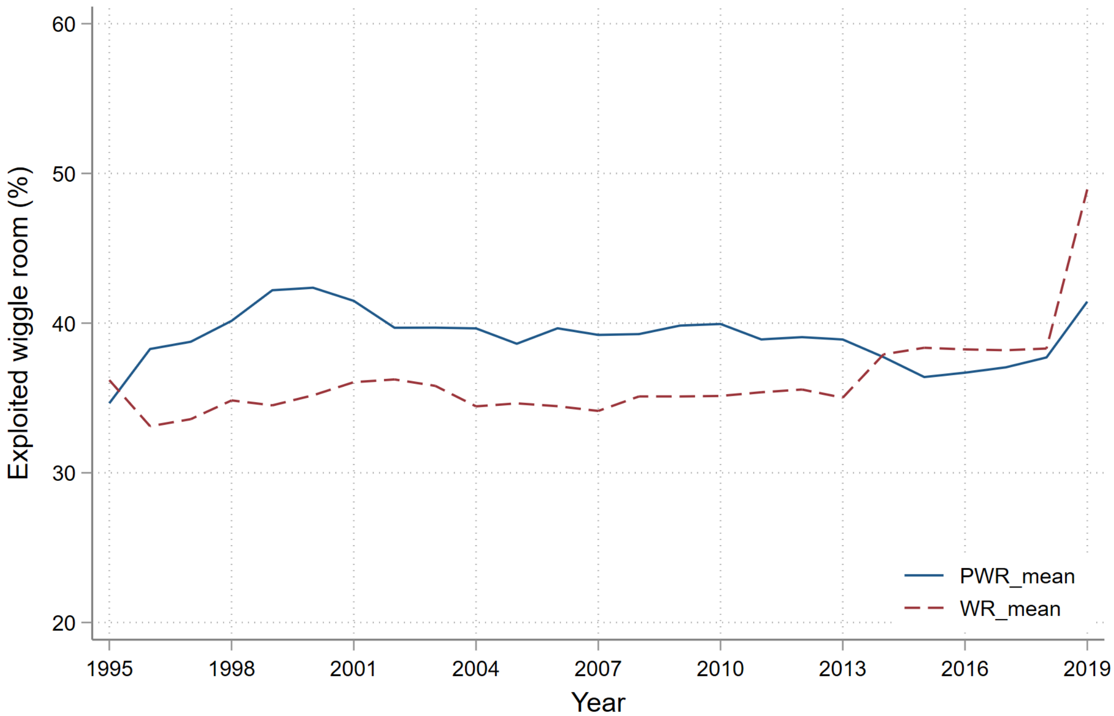
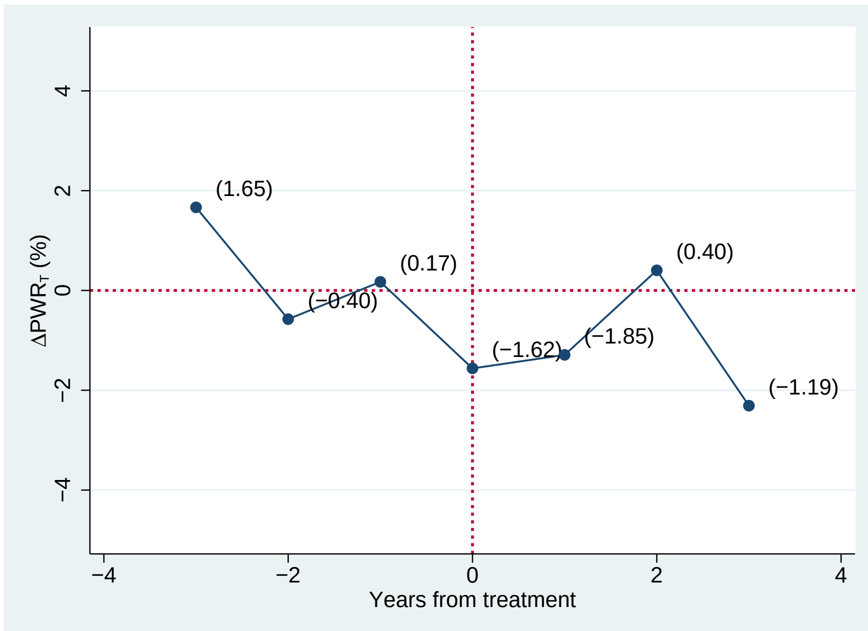
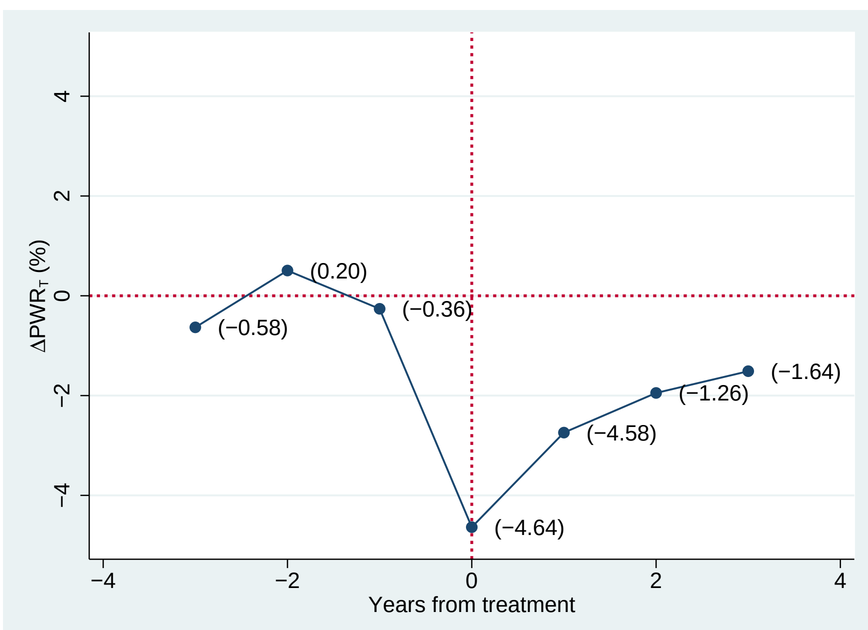


Figure 2: Changes in PWR around financial adviser misconduct
The figure depicts the average treatment effect that employing an adviser who discloses misconduct has on PWR. In the first panel, treatment is any type of disclosed misconduct. In the second panel, treatment are the disclosers that cause the adviser's firing. Coefficients are obtained via nearest neighbor propensity score matching. The control group is estimated using year dummies and several investor characteristics. The sample spans from 2007 to 2015 and covers all institutional investors for which a match with FINRA's BrokerCheck can be established. All variables are described in Table 1. Robust z-statistics are in parentheses (Abadie and Imbens, 2006, 2016).



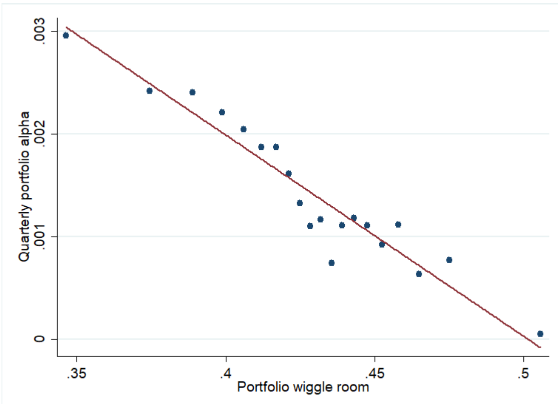
(a) Treatment: Any



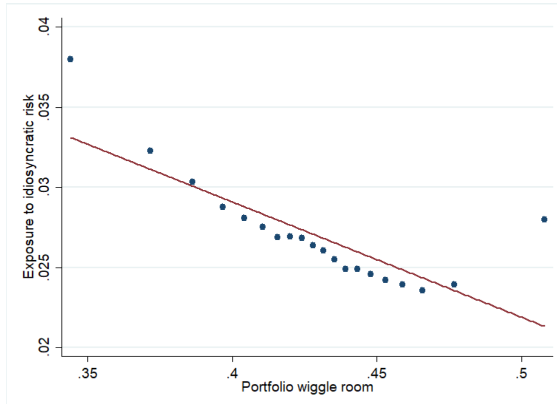
(b) Treatment: Fired

Figure 3: PWR and exposure to idiosyncratic risk

The figure depicts a scatter plot of exploited PWR and measures of portfolio performance, namely quarterly portfolio alphas and exposure to idiosyncratic risk. Both panels control for investor characteristics, time (quarter) fixed effects, and exposure to FF-3 factor portfolios. PWR and the performance measures are winsorized at the 5% level. The sample spans from 1995 to 2019, and covers all quarterly portfolio holdings of institutional investors for which a minimum of 8 observations are available. All variables are described in Table 1.



(a) Portfolio alpha



(b) Exposure to idiosyncratic risk

Tables

Table 1: Variable definitions

Panel A: Institutional investor level variables

#Advisers	Total number of financial advisers employed by an institutional investor during a year	Egan et al. (2019)
Dedicated	Dedicated investors, i.e., those that have a long-term horizon, hold only a limited number of firms in their portfolios, and do not react much to current earning news	Bushee (1998)
Duration	Weighted average of quarters a firm is part of investor's holding for the past 5 years, i.e., average portfolio duration as described in Cremers and Pareek (2015)	13F, CRSP
∅Exam_63	Percentage of employed advisers that have passed the Series 63 Uniform Securities Agent State Law Examination	Egan et al. (2019)
∅Exam_65	Percentage of employed advisers that have passed the Series 65 Uniform Investment Adviser Law Exam	Egan et al. (2019)
∅Exam_66	Percentage of employed advisers that have passed the Series 66 Uniform Combined State Law Examination	Egan et al. (2019)
∅Experience	Average years of experience that the employed financial advisers have	Egan et al. (2019)
Fired_past	Indicator for an institutional investor who employs one or more financial advisers that were fired by their previous employer following a disclosure of misconduct	Egan et al. (2019)
Idiosyn-cratic risk	Exposure to idiosyncratic risk, relative to the Fama-French 3 factor portfolio (Winsorized at 1%), computed as described in Ang et al. (2006)	13F, CRSP
ln(Assets)	Logarithm of the total assets under management of an investor	13F, CRSP
ln(#Stocks)	Logarithm of the number of different stocks an investor holds	13F
Loss	Indicator for an institutional investor who experienced a negative return in the previous quarter	13F
Low/High TO	indicator for below first quartile / above third quartile of investor quarterly TO	13F
PWR	Exploited portfolio WR, computed as the weighted average of the holdings' WR for each quarter	Author
PWR^{buys}	Exploited portfolio WR of the stocks that an investor buys at the end of a quarter	Author
PWR^{exit}	Exploited portfolio WR of the stocks that an investor exits at the end of a quarter	Author
PWR^{init}	Exploited portfolio WR of the stocks that represent the initiating trades of an investor at the end of a quarter	Author
$\Delta\text{PWR}^{noTrade}$	% difference between the investor's current PWR and the PWR she would have had the previous quarter if she did not rebalance her holdings	Author
PWR^{sell}	Exploited portfolio WR of the stocks that an investor sells at the end of a quarter	Author

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QIX	Quasi-indexers, i.e., investors that exhibit high diversification and low turnover, consistent with a buy-and-hold strategy	(Bushee, 1998)
short-/long-term	Indicator for below first quartile / above third quartile of average holding period, computed as described in Cremers and Pareek (2015)	13F
#qtrs	Number of quarters a given investor is in the dataset	13F
Ret (qtr, %)	Quarterly portfolio returns in %, assuming that all trades occur at the end of a given period (Winsorized at 1%)	13F
Ret vola	Volatility of quarterly returns for a given investor	13F, CRSP
Spec	Indicator for investors that are specialized, i.e., hold firms from at most two different industries (2-digit SIC codes)	13F, Compustat
TO	Quarterly portfolio turnover of holdings, as described in Carhart (1997)	13F
Transient	Transient investors, i.e., those that exhibit high diversification, high turnover, and react strongly to current earning news	Bushee (1998)
WRcov	% portfolio holdings for which WR can be computed in the respective quarter	Author
α	Abnormal return, computed as the intercept of a Fama-French 3 factor (FF-3) regression, using rolling exposures to the factor portfolios from the previous 12 quarters (Winsorized at 1%)	Fama and French (1996)
β_{CMA}	Exposure to the FF-5 conservative-minus-aggressive portfolio, computed using a rolling 12 quarters window (Winsorized at 1%)	Fama and French (2015)
β_{HML}	Exposure to the FF-3 high-minus-low portfolio, computed using a rolling 12 quarters window (Winsorized at 1%)	Fama and French (1996)
β_{MKT}	Exposure to the FF-3 market portfolio, computed using a rolling 12 quarters window (Winsorized at 1%)	Fama and French (1996)
β_{RMW}	Exposure to the FF-3 robust-minus-weak portfolio, computed using a rolling 12 quarters window (Winsorized at 1%)	Fama and French (2015)
β_{SMB}	Exposure to the FF-3 small-minus-big portfolio, computed using a rolling 12 quarters window (Winsorized at 1%)	Fama and French (1996)
σ_{PWR}	Time series volatility of quarterly PWR, for the period a given investor is in the dataset	Author

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Panel B: Firm level variables		
CashETR	Long-term effective cash tax rate, that captures the average cah taxes paid per dollar of pre-tax earnings over five years, as described in Dyreng et al. (2008)	Compustat
DQ	Disaggregation quality of financial statements, which captures the level of detail with which anual reports are presemted, as described in Chen et al. (2015)	Compustat
DTAX	Discretionary permanent tax differences, which capture the residual after estimating the permanent book-tax differences, as described in Frank et al. (2009)	Compustat
EM	Earnings management proxy, computed as the average industry-year ranking of discretionary accruals using the following models for estimated total accruals: Dechow et al. (1995), Jones (1991), and Kothari et al. (2005)	Compustat
highVIX	Indicator for quarters when the mean VIX index lies above the 90th percentile	FRED
Just beat	Indicator for beating quarterly median analyst forecasts by no more than 1 USD cent, computed according to Bhojraj et al. (2009)	I/B/E/S
$\text{Sent}^{\perp}$	Quarterly average of orthogonalized market sentiment, as described in Baker and Wurgler (2006)	Baker and Wurgler (2006)
#Tax havens	Indicator for above industry-average number of subsidiaries in tax haven countries, scaled by the logarithm of firms' assets	Dyreng and Lindsey (2009)
∅VIX	Quarterly average of the CBOE Volatility Index (VIX)	FRED
WR	Exploited regulatory "*wiggle room*" (WR), computed as the average industry-year percentile rankings of: earnings management (EM), *minus* disaggregation quality of financial statements (DQ), long-term effective cash tax rate (CashETR), and discretionary permanent tax differences (DTAX), together with an indicator for above industry-average number of subsidiaries in tax haven countries (scaled by firm size), and an indicator for beating median analyst forecasts by no more than 1 USD cent (beat)	Author
#WRcomp	Number of proxies that are available for the computation of WR for a given fiscal year	Author

Table 2: Firm-level summary statistics
The table provides descriptive statistics for firm-level WR and for the proxies used for its computation, displayed in absolute terms (instead of percentile rankings). The sample spans from 1995 to 2019 and covers all firms in the Compustat - I/B/E/S universe. All variables are described in Table 1.

	Obs	mean	p25	p50	p75	sd	min	max
CashETR	244,709	0.61	0.53	0.61	0.71	0.18	0.00	1.00
DQ	265,392	0.72	0.68	0.74	0.76	0.07	0.16	0.96
DTAX	255,005	0.01	-0.00	0.01	0.03	0.07	-2.87	4.15
EM	263,914	0.43	0.39	0.42	0.46	0.08	0.02	1.00
Just beat	260,604	0.01	0.00	0.00	0.01	0.03	0.00	1.00
#Tax havens	202,505	6.54	2.96	5.71	9.46	4.77	-0.67	101.97
WR	265,400	0.39	0.36	0.39	0.42	0.06	0.00	1.00
#WRcomp	265,400	4.15	3.85	4.21	4.57	0.57	1.00	6.00

Table 3: Investor-level summary statistics
The table provides descriptive statistics for all variables of interest on the institutional investor portfolio level. Performance variables have been winsorized at the 1% level. The sample spans from 1995 to 2019, and covers all quarterly portfolio holdings of institutional investors for which a minimum of 8 observations are available. All variables are described in Table 1.

	Obs	mean	p25	p50	p75	sd	min	max
Duration	245,356	6.02	3.24	5.50	8.33	3.42	0.38	20.00
Idiosyncratic risk	234,565	0.03	0.01	0.02	0.03	0.02	0.00	0.15
ln(Assets)	245,927	6.27	5.08	5.96	7.24	1.75	-6.34	14.79
ln(#Stocks)	245,927	4.59	3.78	4.55	5.38	1.37	0.69	8.80
PWR	245,927	0.39	0.36	0.39	0.42	0.05	0.00	0.95
#qtrs in sample	245,927	58.75	33.00	58.00	87.00	28.89	8.00	100.00
Ret (qtr, %)	245,927	2.20	-1.60	2.92	7.04	8.67	-27.27	28.05
Return volatility	245,927	0.09	0.07	0.08	0.10	0.04	0.01	0.93
Spec	245,927	0.03	0.00	0.00	0.00	0.16	0.00	1.00
TO	244,346	0.12	0.03	0.07	0.16	0.13	0.00	1.09
WRcov (%)	245,927	0.85	0.83	0.95	0.99	0.23	0.00	1.00
α	192,047	0.00	-0.01	-0.00	0.01	0.02	-0.07	0.08
β_{HML}	191,913	0.02	-0.15	0.01	0.19	0.38	-1.55	1.54
β_{MKT}	192,176	0.98	0.84	0.96	1.09	0.27	-0.02	2.29
β_{SMB}	191,875	0.15	-0.13	0.04	0.33	0.47	-1.10	2.53
σ_{PWR}	245,927	0.15	0.13	0.15	0.16	0.03	0.00	0.67

Table 4: Investor horizon and turnover
The table provides results of regressions of PWR on investor horizon and turnover (TO). Short- and long-term are defined as the first and fourth quartile of the portfolio duration distribution. Low and high TO are defined as the first and last quartile of TO distribution. The base category consists of the respectively remaining investors. All regressions control for investor characteristics, time (quarter) fixed effects, and exposure to FF-3 factor portfolios. Standard errors are multi-way clustered along quarter and investor, and t-statistics are presented in parentheses. ***, **, and * indicate that the parameter estimate is significantly different from zero at the 1%, 5%, and 10% level, respectively. The sample spans from 1995 to 2019, and covers all quarterly portfolio holdings of institutional investors for which a minimum of 8 observations are available. All variables are described in Table 1.

	Investment horizon		Turnover	
	(1)	(2)	(3)	(4)
Short-term	-0.361***	-0.362***		
	(-3.78)	(-3.82)		
Long-Term	0.198*	0.199*		
	(2.02)	(2.06)		
Low Turnover			0.156	0.156
			(1.81)	(1.82)
High Turnover			-0.463***	-0.463***
			(-5.53)	(-5.61)
σ_{PWR}		0.402		-0.129
		(0.15)		(-0.05)
β_{HML}	-0.306*	-0.307*	-0.322*	-0.322*
	(-2.03)	(-2.05)	(-2.13)	(-2.15)
β_{MKT}	-0.235	-0.237	-0.246	-0.246
	(-1.38)	(-1.39)	(-1.44)	(-1.44)
β_{SMB}	-1.814***	-1.816***	-1.784***	-1.783***
	(-11.38)	(-11.62)	(-11.04)	(-11.31)
Constant	39.496***	39.439***	39.477***	39.496***
	(163.58)	(96.46)	(164.69)	(93.66)
Observations	192,533	192,533	189,421	189,421
R-squared	0.26	0.26	0.27	0.27
Controls	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes

Table 5: Investor legal type and strategy
The table provides results of regressions of PWR on investor legal type and strategy, as provided in Bushee (1998). The base categories are miscellaneous investors respectively quasi-indexers. All regressions control for investor characteristics, time (quarter) fixed effects, and exposure to FF-3 factor portfolios. Standard errors are multi-way clustered along quarter and investor, and t-statistics are presented in parentheses. ***, **, and * indicate that the parameter estimate is significantly different from zero at the 1%, 5%, and 10% level, respectively. The sample spans from 1995 to 2019, and covers all quarterly portfolio holdings of institutional investors for which a minimum of 8 observations are available. All variables are described in Table 1.

	Legal type		Strategy	
	(1)	(2)	(3)	(4)
Bank	0.372*	0.373*		
	(1.88)	(1.89)		
Corp. pension	0.232	0.234		
	(0.71)	(0.71)		
Invst. advisor	-0.078	-0.078		
	(-0.50)	(-0.50)		
Insurance	0.243	0.245		
	(0.75)	(0.76)		
Public pension	0.421**	0.424**		
	(2.01)	(2.04)		
Endowments	0.048	0.048		
	(0.07)	(0.07)		
Dedicated			-1.847***	-1.844***
			(-5.04)	(-5.09)
Transient			-0.248***	-0.246***
			(-2.76)	(-2.80)
σ_{PWR}		0.473		-0.484
		(0.17)		(-0.17)
β_{HML}	-0.321**	-0.322**	-0.269*	-0.268*
	(-2.16)	(-2.18)	(-1.82)	(-1.83)
β_{MKT}	-0.313*	-0.314*	-0.297*	-0.295*
	(-1.81)	(-1.82)	(-1.71)	(-1.71)
β_{SMB}	-1.862***	-1.864***	-1.808***	-1.806***
	(-11.07)	(-11.39)	(-11.23)	(-11.48)
Constant	39.638***	39.571***	39.652***	39.720***
	(140.79)	(91.31)	(160.82)	(90.96)
Observations	192,264	192,264	189,237	189,237
R-squared	0.26	0.26	0.27	0.27
Controls	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes

Table 6: Changes in PWR following financial adviser misconduct

The table depicts the average treatment effect that employing an adviser who discloses misconduct has on PWR. The outcome variable in models (1) to (3) is the total change in quarterly PWR for the year of treatment. Outcome variables in models (4) to (6) are the total changes in quarterly PWR occurring respectively the year before, the year after, and two years after treatment. Treatment "Any" considers any type of misconduct disclsoed during a given year; "Criminal" considers only disclosures that contain criminal charges; "Fired" considers only disclosures that lead to the firing of the adviser. Data on financial adviser misconduct is described in Egan et al. (2019, 2018). The control group is estimated via nearest neighbor propensity score matching using year dummies and the following investor characteristics, measured on the last available quarter before treatment: #Adivers, β_{HML}, β_{MKT}, β_{SMB}, Duration, ∅Exam_63, ∅Exam_65, ∅Exam_66, ∅Experience, Fired_past, ln(Assets), ln(# Stocks), Loss, and TO. Robust standard errors are computed according to Abadie and Imbens (2006, 2016), and z-statistics are presented in parentheses. ***, **, and * indicate that the parameter estimate is significantly different from zero at the 1%, 5%, and 10% level, respectively. The sample spans from 2007 to 2015 and covers all institutional investors for which a match with FINRA's BrokerCheck can be established. All variables are described in Table 1.

Dependent variable (%):	ΔPWR$_T$			ΔPWR$_{T-1}$	ΔPWR$_{T+1}$	ΔPWR$_{T+2}$
	(1)	(2)	(3)	(4)	(5)	(6)
Type of Financial misconduct:						
Any	-1.562					
	(-1.62)					
Criminal		-1.172***				
		(-8.32)				
Fired			-4.637***	-0.261	-2.742***	-1.947
			(-4.64)	(-0.36)	(-4.58)	(-1.26)
Observations	6035	5067	6057	6047	4844	3728
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 7: Drivers of changes in PWR following financial adviser misconduct

The table depicts the average treatment effect that employing an adviser who discloses misconduct has on the PWR of the investor's trades. The outcome variable in column (1) is the total change in PWR for the year of treatment. For columns (2) to (5) the PWR of the portfolio of traded stocks during each quarter is computed by considering respectively only buys, initiating buys, sells, and exited stocks. The outcome variables are the total yearly differences between the PWR of the stocks traded and the PWR of the stocks held during a quarter. Column (6) reports the total % change in WR for the firms the investor holds at the end of the quarter. Treatment is defined as disclosures that lead to the firing of the adviser. Data on financial adviser misconduct is described in Egan et al. (2019, 2018). The control group is estimated via nearest neighbor propensity score matching using year dummies and the following investor characteristics, measured on the last available quarter before treatment: #Adivers, β_{HML}, β_{MKT}, β_{SMB}, Duration, ∅Exam_63, ∅Exam_65, ∅Exam_66, ∅Experience, Fired_past, ln(Assets), ln(# Stocks), Loss, and TO. Robust standard errors are computed according to Abadie and Imbens (2006, 2016), and z-statistics are presented in parentheses. ***, **, and * indicate that the parameter estimate is significantly different from zero at the 1%, 5%, and 10% level, respectively. The sample spans from 2007 to 2015 and covers all institutional investors for which a match with FINRA's BrokerCheck can be established. All variables are described in Table 1.

Drivers of ΔPWR$_T$ (%):	Initial effect	Buys		Sells		ΔWR
	(1)	(2)	(3)	(4)	(5)	(6)
	ΔPWR_T	$\Delta\text{PWR}_T^{buys}$	$\Delta\text{PWR}_T^{init}$	$\Delta\text{PWR}_T^{sells}$	$\Delta\text{PWR}_T^{exit}$	$\Delta\text{PWR}_T^{noTrade}$
Type of financial misconduct:						
Fired	-4.637***	-2.758***	0.578	-6.394	0.479***	-4.262**
	(-4.64)	(-4.91)	(0.82)	(-1.49)	(3.56)	(-3.11)
Observations	6057	6055	6055	6055	6055	6055
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 8: Institutional investor preferences and changes in firm behavior
The table provides results of firm-level regressions of firms' exploited wiggle room (WR_Firm) ((1) and (2)) and the absolute difference between WR_Firm and the exogenous PWR (PWR_Exog) of the acquiring institutional investor ((3) and (4)). To construct PWR_Exog, only institutional investors are considered that either own a block of at least 5% or are among the largest five institutional owners of a firm. $\varnothing PWR_{t-1}$ captures the value-weighted PWR of the institutional investors of a firm. Post Acquisition is a dummy for the 8 quarters after a merger between institutional investors happens. Columns (2) and (4) also control for total institutional ownership, the log of the number of institutional owners, and the firm's market capitalization in the previous quarter. The first two models cover the full sample of firms. The last two models look only at firms that are in the portfolio of institutional investors that are targeted in a merger. Institutional investors' mergers are from Lewellen and Lowry (2021). All regressions include quarter and industry fixed effects The sample spans from 1995 to 2017, and covers all quarterly portfolio holdings of institutional investors for which a minimum of 8 observations are available. Only two years of data are kept after the acquisition takes place. All variables are described in Table 1.

Dependent variable (%):	WR_Firm		$\|WR\_firm_{t-1}-PWR\_exog_{t-1}\|$	
	(1)	(2)	(3)	(4)
$\varnothing PWR_{t-1}$(%)	1.48***	1.56***	-0.09	0.01
	(30.04)	(28.42)	(-0.97)	(0.16)
Post Acquisition			-1.26***	-1.19***
			(-3.18)	(-3.18)
$\varnothing Duration_{t-1}$		0.09***		-0.28***
		(2.93)		(-3.77)
Total IO_{t-1}(%)		0.00		0.00
		(0.63)		(1.07)
Log #Inst $invstors_{t-1}$		-0.93***		-1.06***
		(-5.69)		(-2.86)
Log Market $Cap._{t-1}$		0.26**		0.07
		(2.26)		(0.31)
Constant	-21.12***	-26.39***	19.11***	18.47***
	(-11.23)	(-10.75)	(5.37)	(3.94)
Observations	505,136	500,811	23,193	23,193
R-squared	0.08	0.09	0.09	0.10
Quarter FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes

Table 9: Excess returns and portfolio alphas

The table provides results of regressions of abnormal performance measures on PWR. The first three models are regressions of quarterly excess returns on PWR, controlling for exposure to the FF-3 portfolios. The last three are regressions of portfolio alphas on PWR. All regressions control for investor characteristics, and time (quarter) fixed effects. Standard errors are multi-way clustered along quarter and investor, and t-statistics are presented in parentheses. ***, **, and * indicate that the parameter estimate is significantly different from zero at the 1%, 5%, and 10% level, respectively. The sample spans from 1995 to 2019, and covers all quarterly portfolio holdings of institutional investors for which a minimum of 8 observations are available. All variables are described in Table 1.

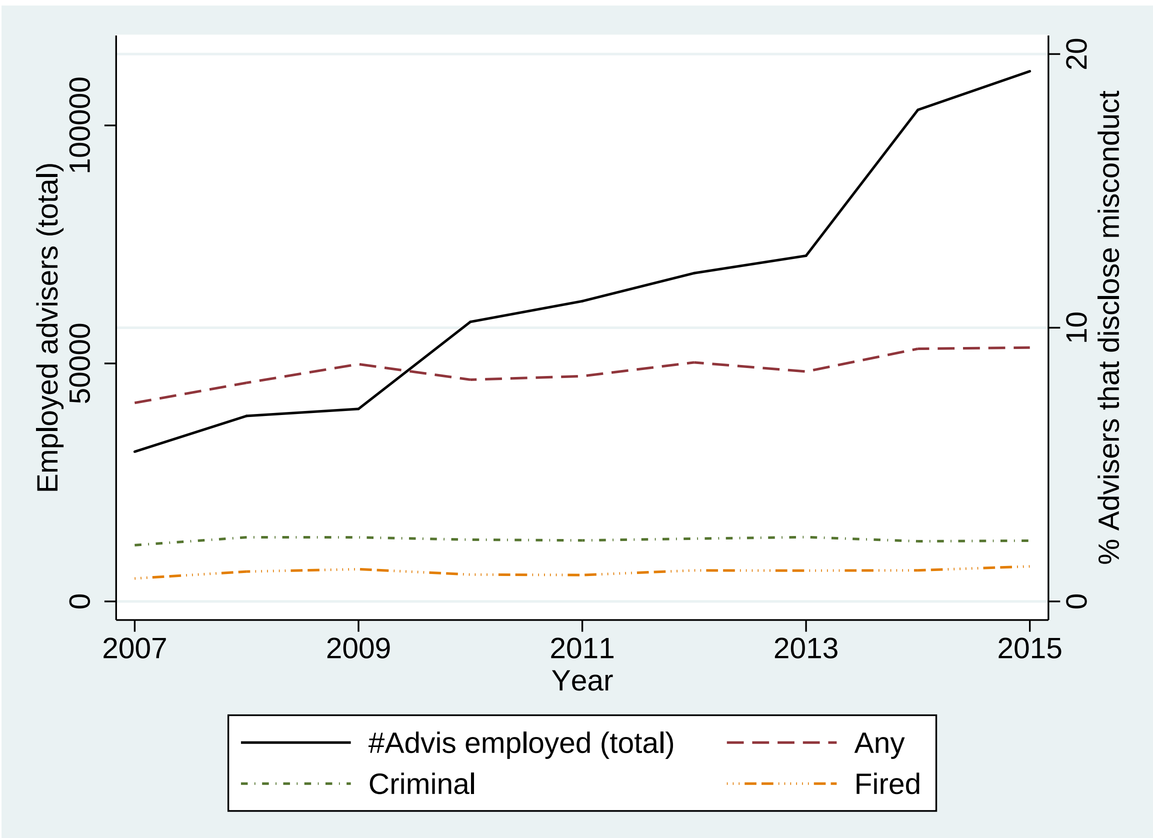
Dependent variable:	Excess returns			α		
	(1)	(2)	(3)	(4)	(5)	(6)
PWR	-0.026**	-0.023*	-0.028**	-0.016***	-0.017***	-0.017***
	(-2.18)	(-1.96)	(-2.36)	(-5.01)	(-5.23)	(-5.30)
β_{HML}	-0.001	-0.001	-0.001			
	(-0.20)	(-0.16)	(-0.15)			
β_{MKT}	0.000	-0.000	0.000			
	(0.10)	(-0.03)	(0.01)			
β_{SMB}	0.001	0.001	0.001			
	(0.40)	(0.27)	(0.44)			
Constant	0.034***	0.033***	0.035***	0.008***	0.008***	0.008***
	(4.32)	(4.36)	(4.44)	(4.67)	(4.69)	(4.81)
Observations	187,994	186,998	187,440	197,485	193,323	196,764
R-squared	0.77	0.78	0.78	0.05	0.05	0.05
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Horizon and TO	No	Yes	No	No	Yes	No
F13type Strategy	No	No	Yes	No	No	Yes

Table 10: Exposure to idiosyncratic risk
The table provides results of regressions of exposure to idiosyncratic risk on PWR after controlling for exposure to the FF-3 portfolios. All regressions control for investor characteristics, and time (quarter) fixed effects. Standard errors are multi-way clustered along quarter and investor, and t-statistics are presented in parentheses. ***, **, and * indicate that the parameter estimate is significantly different from zero at the 1%, 5%, and 10% level, respectively. The sample spans from 1995 to 2019, and covers all quarterly portfolio holdings of institutional investors for which a minimum of 8 observations are available. All variables are described in Table 1.

Dependent variable:	Idiosyncratic risk			
	(1)	(2)	(3)	(4)
PWR	-0.045***	-0.050***	-0.044***	-0.045***
	(-6.95)	(-7.39)	(-6.87)	(-7.24)
σ_{PWR}		0.103***	0.099***	0.099***
		(10.03)	(9.71)	(9.64)
Constant	0.076***	0.063***	0.057***	0.056***
	(27.19)	(17.79)	(16.68)	(16.63)
Observations	250,410	247,271	236,562	219,079
R-squared	0.35	0.35	0.37	0.40
Controls	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes
Horizon and TO	No	No	Yes	No
F13type Strategy	No	No	No	Yes

Appendix Figures

Figure A1: Number of disclosed misconduct cases by year
The figure depicts the distribution of the various misconduct types over time. #Advis employed depicts the total number of financial advisers that were employed by the institutional investors in the sample during a given year; Any depicts the % of advisers that disclosed misconduct cases during a given year; Criminal depicts the % of advisers that disclosed criminal misconduct cases; Fired depicts the % of advisers that disclosed misconduct cases that lead to the firing of the adviser. Data on financial adviser misconduct is described in Egan et al. (2019, 2018). The sample spans from 2007 to 2015 and covers all institutional investors for which a match with FINRA's BrokerCheck can be established. All variables are described in Table 1.



Appendix Tables

Table A1: Correlation of individual WR components

The table provides correlations between the industry-year rankings of yearly exploitation measures computed on a firm level. ***, **, and * indicate that the parameter estimate is significantly different from zero at the 1%, 5%, and 10% level, respectively. The sample spans from 1995 to 2019 and covers all firms in the Compustat - I/B/E/S universe. All variables are described in Table 1.

	WR	CashETR	DQ	DTAX	EM	Just beat	#Tax havens
WR	1.00						
CashETR	0.49***	1.00					
DQ	0.55***	0.04***	1.00				
DTAX	0.48***	0.05***	-0.01*	1.00			
EM	0.39***	0.00	-0.03***	-0.05***	1.00		
Just beat	0.24***	-0.00	-0.01***	0.00	0.01***	1.00	
#Tax havens	0.61***	0.01	0.09***	0.02***	-0.12***	-0.01**	1.00

Table A2: Investor-level summary statistics - Matched and full samples

The table compares descriptive statistics for all variables of interest between the matched Thomson 13F - FINRA BrokerCheck sample and the full 13F sample. Performance variables have been winsorized at the 1% level. The sample spans from 2007Q1 to 2015Q4, and covers all quarterly portfolio holdings of institutional investors for which a minimum of 8 observations are available. All variables are described in Table 1.

	Matched sample				Full sample			
	Obs	mean	p50	sd	Obs	mean	p50	sd
Duration	40719	6.68	6.43	3.20	96374	6.00	5.48	3.42
Idiosyncratic risk	40514	0.02	0.02	0.02	94817	0.03	0.02	0.02
ln(Assets)	40763	6.15	5.80	1.62	96584	6.23	5.91	1.79
ln(#Stocks)	40763	4.70	4.63	1.06	96585	4.51	4.47	1.40
PWR	40763	0.43	0.43	0.04	96585	0.42	0.42	0.05
#qtrs in sample	40763	29.89	34.00	7.98	96585	28.69	34.00	8.53
Ret (qtr, %)	40763	1.46	2.41	9.36	96585	1.50	2.46	10.22
Return volatility	40763	0.09	0.09	0.03	96585	0.10	0.10	0.04
Spec	40763	0.01	0.00	0.10	96585	0.03	0.00	0.16
TO	40712	0.10	0.06	0.10	95841	0.13	0.08	0.14
WRcov (%)	40763	0.86	0.97	0.24	96585	0.89	0.98	0.21
α	33863	0.00	0.00	0.01	77152	0.00	0.00	0.02
β_{HML}	33863	0.01	0.01	0.36	77152	0.01	0.01	0.44
β_{MKT}	33863	0.97	0.97	0.25	77152	1.01	0.98	0.31
β_{SMB}	33863	0.13	0.05	0.48	77152	0.20	0.08	0.59
σ_{PWR}	40763	0.15	0.15	0.02	96585	0.15	0.15	0.02

Table A3: Predicting assignment to treatment

The table provides results of logit regressions of a treatment indicator on investor characteristics. Treatment "Any" considers any type of misconduct disclsoed during a given year; "Criminal" considers only disclosures that contain criminal charges; "Fired" considers only disclosures that lead to the firing of the adviser. Data on financial adviser misconduct is described in Egan et al. (2019, 2018). Standard errors are multi-way clustered along quarter and investor, and t-statistics are presented in parentheses. ***, **, and * indicate that the parameter estimate is significantly different from zero at the 1%, 5%, and 10% level, respectively. The sample spans from 2007 to 2015 and covers all institutional investors for which a match with FINRA's BrokerCheck can be established. All variables are described in Table 1.

	Type of treatment:					
	(1) Any		(2) Criminal		(3) Fired	
#Advisers	0.014***	(5.24)	0.003***	(4.33)	0.005***	(9.94)
β_{HML}	0.231	(0.52)	0.722	(0.33)	-0.271	(-0.65)
β_{MKT}	-0.896*	(-2.07)	-2.263	(-1.30)	-0.084	(-0.11)
β_{SMB}	-0.049	(-0.15)	-0.002	(-0.00)	-0.901*	(-2.39)
Duration	-0.081	(-1.05)	0.005	(0.04)	-0.025	(-0.40)
∅Exam_63	1.065***	(3.47)	0.945*	(2.03)	0.788	(1.59)
∅Exam_65	0.855	(1.82)	0.720	(1.16)	0.939*	(2.03)
∅Exam_66	2.243***	(4.81)	3.056***	(4.99)	2.625***	(4.31)
∅Experience	-0.015	(-0.53)	-0.050	(-0.56)	-0.038	(-0.99)
Fired_past	9.426***	(6.01)	11.786***	(5.41)	9.574***	(6.31)
ln(Assets)	-0.445***	(-8.08)	-0.337	(-1.29)	-0.292*	(-2.15)
Loss	0.574	(1.37)	-0.823	(-0.83)	0.205	(0.17)
TO	-1.503	(-1.24)	-1.418	(-0.24)	-0.003	(-0.00)
ln(#Stocks)	0.465**	(2.61)	1.155*	(2.56)	0.788**	(2.76)
Constant	-4.167***	(-4.09)	-9.314***	(-3.49)	-8.209***	(-4.65)
Observations	6035		5067		6057	
Year dummies	Yes		Yes		Yes	

Table A4: Balancing of treatment and control group
The table provides mean comparison for the treated and control groups obtained by the propensity score matching. Treatment "Any" considers any type of misconduct disclsoed during a given year; "Fired" considers only disclosures that lead to the termination of the employment contract between the adviser and her employer. Data on financial adviser misconduct is described in Egan et al. (2019, 2018). The control group is estimated via nearest neighbor propensity score matching using year dummies and the following investor characteristics, measured on the last available quarter before treatment: #Adivers, β_{HML}, β_{MKT}, β_{SMB}, Duration, ∅Exam_63, ∅Exam_65, ∅Exam_66, ∅Experience, Fired_past, ln(Assets), ln(# Stocks), Loss, and TO. Standard errors are multi-way clustered along year and investor. The sample spans from 2007 to 2015 and covers all institutional investors for which a match with FINRA's BrokerCheck can be established. All variables are described in Table 1.

	Type of treatment:					
	Any			Fired		
	Treatment	Control	(t stat)	Treatment	Control	(t stat)
#Advisers	258.23	255.07	(0.10)	530.01	521.57	(0.09)
β_{HML}	0.03	0.06	(-1.20)	0.03	0.06	(-0.82)
β_{MKT}	0.92	0.94	(-0.85)	0.90	0.91	(-0.20)
β_{SMB}	0.04	0.02	(0.64)	0.02	-0.01	(0.65)
Duration	6.74	7.02	(-1.10)	6.76	6.81	(-0.14)
∅Exam_63	0.62	0.54	(3.22)	0.66	0.66	(-0.19)
∅Exam_65	0.51	0.57	(-2.26)	0.50	0.46	(1.10)
∅Exam_66	0.36	0.33	(0.87)	0.38	0.43	(-1.13)
∅Experience	6.91	6.34	(1.77)	6.94	6.41	(1.27)
Fired_past	0.01	0.01	(-0.39)	0.02	0.01	(1.41)
ln(Assets)	7.08	7.85	(-2.82)	7.25	7.41	(-0.58)
Loss	0.26	0.23	(0.65)	0.19	0.28	(-1.35)
TO	0.09	0.08	(1.08)	0.09	0.09	(-0.14)
ln(#Stocks)	5.87	5.78	(0.64)	6.16	6.17	(-0.03)
Observations	160	5875		75	5982	
Year Dummies	Yes	Yes		Yes	Yes	

Table A5: Excess returns and portfolio alphas

The table provides results of regressions of excess performance measures on PWR. The first three models are regressions of quarterly excess returns on PWR, controlling for exposure to the FF-5 portfolios. The last three are regressions of portfolio alphas on PWR. All regressions control for investor characteristics, and time (quarter) fixed effects. Standard errors are multi-way clustered along quarter and investor, and t-statistics are presented in parentheses. ***, **, and * indicate that the parameter estimate is significantly different from zero at the 1%, 5%, and 10% level, respectively. The sample spans from 1995 to 2019, and covers all quarterly portfolio holdings of institutional investors for which a minimum of 8 observations are available. All variables are described in Table 1.

Dependent variable:	Excess returns			α		
	(1)	(2)	(3)	(4)	(5)	(6)
PWR	-0.024*	-0.023*	-0.025**	-0.020***	-0.019***	-0.019***
	(-1.98)	(-1.92)	(-2.14)	(-5.06)	(-4.94)	(-5.08)
β_{HML}	-0.002	-0.002	-0.002			
	(-0.53)	(-0.48)	(-0.48)			
β_{MKT}	0.002	0.001	0.001			
	(0.35)	(0.28)	(0.33)			
β_{SMB}	0.003	0.002	0.003			
	(0.90)	(0.79)	(0.91)			
β_{RMW}	-0.002	-0.001	-0.002			
	(-0.70)	(-0.63)	(-0.71)			
β_{CMA}	-0.001	-0.000	-0.000			
	(-0.22)	(-0.18)	(-0.18)			
Constant	0.032***	0.031***	0.032***	0.012***	0.011***	0.011***
	(4.37)	(4.39)	(4.44)	(6.32)	(6.13)	(5.81)
Observations	186,777	185,825	186,304	197,470	193,331	196,714
R-squared	0.78	0.78	0.78	0.04	0.05	0.05
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Horizon and TO	No	Yes	No	No	Yes	No
F13type Strategy	No	No	Yes	No	No	Yes

Table A6: Exposure to idiosyncratic risk

The table provides results of regressions of exposure to idiosyncratic risk on PWR after controlling for exposure to the FF-5 portfolios. All regressions control for investor characteristics, and time (quarter) fixed effects. Standard errors are multi-way clustered along quarter and investor, and t-statistics are presented in parentheses. ***, **, and * indicate that the parameter estimate is significantly different from zero at the 1%, 5%, and 10% level, respectively. The sample spans from 1995 to 2019, and covers all quarterly portfolio holdings of institutional investors for which a minimum of 8 observations are available. All variables are described in Table 1.

Dependent variable:	Idiosyncratic risk			
	(1)	(2)	(3)	(4)
PWR	-0.072***	-0.078***	-0.069***	-0.070***
	(-7.20)	(-7.33)	(-6.80)	(-7.18)
σ_{PWR}		0.147***	0.146***	0.134***
		(8.59)	(8.52)	(7.99)
Constant	0.122***	0.102***	0.091***	0.089***
	(24.48)	(16.93)	(15.58)	(15.99)
Observations	250,371	246,858	236,119	218,230
R-squared	0.25	0.23	0.24	0.25
Controls	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes
Horizon and TO	No	No	Yes	No
F13type Strategy	No	No	No	Yes

Table A7: Portfolio performance and risk measures - Individual WR proxies
The table provides results of regressions of abnormal performance measures and exposures to idiosyncratic risk on the individual proxies for regulatory wiggle room exploitation. These are first computed on the firm level, where I assign percentile rankings within a given industry-year. Second, they are brought to a quarterly portfolio level through the weighted average across an investor's holdings. The dependent variables for models (1) and (2) are quarterly excess returns, for (3) and (4) portfolio alphas, and for (5) and (6) exposure to idiosyncratic risk. All regressions control for investor characteristics, and time (quarter) fixed effects. Standard errors are multi-way clustered along quarter and investor, and t-statistics are presented in parentheses. ***, **, and * indicate that the parameter estimate is significantly different from zero at the 1%, 5%, and 10% level, respectively. The sample spans from 1995 to 2019, and covers all quarterly portfolio holdings of institutional investors for which a minimum of 8 observations are available. All variables are described in Table 1.

Dependent variable:	Excess returns		α		Idiosyncratic risk	
	(1)	(2)	(3)	(4)	(5)	(6)
CashETR	-0.007	-0.006	0.003*	0.004*	0.010***	0.011***
	(-1.35)	(-1.30)	(1.81)	(1.95)	(4.12)	(4.84)
DQ	-0.008	-0.008	-0.005*	-0.004*	-0.006**	-0.007**
	(-1.34)	(-1.35)	(-1.78)	(-1.72)	(-2.20)	(-2.46)
DTAX	0.003	0.003	-0.001	-0.001	-0.008***	-0.007***
	(0.72)	(0.67)	(-0.89)	(-0.90)	(-6.37)	(-6.14)
EM	-0.005	-0.003	0.002	0.003	0.050***	0.050***
	(-0.47)	(-0.32)	(0.82)	(0.96)	(15.30)	(15.63)
Just beat	-0.005	0.001	0.005	0.006	0.039***	0.037***
	(-0.41)	(0.11)	(1.09)	(1.11)	(7.00)	(6.83)
#Tax havens	-0.006**	-0.007**	-0.003***	-0.003***	-0.017***	-0.016***
	(-2.19)	(-2.41)	(-2.84)	(-3.09)	(-7.46)	(-7.45)
Constant	0.030***	0.030***	0.002	0.002	0.032***	0.032***
	(2.73)	(2.68)	(0.73)	(0.86)	(8.25)	(8.77)
Observations	131,425	131,515	135,327	137,621	168,488	171,297
R-squared	0.81	0.80	0.05	0.05	0.39	0.41
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Horizon and TO	Yes	No	Yes	No	Yes	No
F13type Strategy	No	Yes	No	Yes	No	Yes

Table A8: Portfolio performance and risk measures - Individual WR proxies
The table provides results of regressions of exposure to idiosyncratic risk after controlling for the FF-5 factors on the individual proxies for regulatory wiggle room exploitation. These are first computed on the firm level, where I assign percentile rankings within a given industry-year. Second, they are brought to a quarterly portfolio level through the weighted average across an investor's holdings. The dependent variables for models (1) and (2) are quarterly excess returns, for (3) and (4) portfolio alphas, and for (5) and (6) exposure to idiosyncratic risk. All regressions control for investor characteristics, and time (quarter) fixed effects. Standard errors are multi-way clustered along quarter and investor, and t-statistics are presented in parentheses. ***, **, and * indicate that the parameter estimate is significantly different from zero at the 1%, 5%, and 10% level, respectively. The sample spans from 1995 to 2019, and covers all quarterly portfolio holdings of institutional investors for which a minimum of 8 observations are available. All variables are described in Table 1.

Dependent variable:	Excess returns		α		Idiosyncratic risk	
	(1)	(2)	(3)	(4)	(5)	(6)
CashETR	-0.007	-0.007	0.005*	0.006*	0.022***	0.023***
	(-1.25)	(-1.15)	(2.22)	(2.50)	(5.05)	(5.46)
DQ	-0.005	-0.005	-0.009**	-0.008**	-0.018**	-0.019**
	(-0.92)	(-1.00)	(-3.23)	(-3.08)	(-3.10)	(-3.40)
DTAX	0.004	0.003	0.002	0.001	-0.012***	-0.011***
	(0.88)	(0.77)	(1.33)	(1.14)	(-4.98)	(-4.79)
EM	-0.008	-0.007	0.016***	0.018***	0.070***	0.068***
	(-0.88)	(-0.75)	(4.01)	(4.37)	(12.62)	(12.22)
Just beat	-0.013	-0.006	0.016*	0.015*	0.054***	0.047***
	(-0.95)	(-0.42)	(2.61)	(2.55)	(4.91)	(4.13)
#Tax havens	-0.006	-0.006	-0.004***	-0.004***	-0.024***	-0.020***
	(-1.79)	(-1.91)	(-3.77)	(-3.88)	(-7.64)	(-7.33)
Constant	0.029*	0.029*	-0.000	-0.001	0.053***	0.055***
	(2.59)	(2.56)	(-0.03)	(-0.34)	(7.90)	(8.22)
Observations	131,034	131,122	135,215	137,459	167,614	170,347
R-squared	0.81	0.80	0.06	0.06	0.21	0.23
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Horizon and TO	Yes	No	Yes	No	Yes	No
F13type Strategy	No	Yes	No	Yes	No	Yes

Table A9: Market sentiment and uncertainty

The table provides results of regressions of quarterly PWR on the average orthogonalized market sentiment and VIX during the current quarter. Sentiment is interacted with dummy variables that identify investors by investment horizon through average portfolio duration, trading intensity through quarterly prtfolio turnover (TO), and general investment strategy from Bushee (1998). All regressions control for the volatility of PWR, portfolio MA, exposure to FF-3 factor portfolios, investor characteristics, and seasonality via quarter-of-year fixed effects. Standard errors are multi-way clustered along quarter and investor, and t-statistics are presented in parentheses. ***, **, and * indicate that the parameter estimate is significantly different from zero at the 1%, 5%, and 10% level, respectively. The sample spans from 1995 to 2019, and covers all quarterly portfolio holdings of institutional investors for which a minimum of 8 observations are available. All variables are described in Table 1.

Dependent variable:	PWR(%)					
	$\text{Sentiment}^{\perp}$			VIX		
	(1)	(2)	(3)	(4)	(5)	(6)
$\text{Sent}_t^{\perp}$	0.009***	0.009***	0.009**			
	(5.16)	(4.39)	(3.19)			
$\varnothing\text{VIX}_t$				0.003***	0.003***	0.003***
				(4.65)	(4.63)	(4.62)
$\varnothing\text{VIX}_t^2$				-0.000***	-0.000***	-0.000***
				(-4.44)	(-4.42)	(-4.42)
short-term × $\text{Sent}_t^{\perp}$	-0.005***					
	(-3.88)					
long-term × $\text{Sent}_t^{\perp}$	0.000					
	(0.35)					
low TO × $\text{Sent}_t^{\perp}$		0.002				
		(1.67)				
high TO × $\text{Sent}_t^{\perp}$		-0.003**				
		(-2.83)				
DED × $\text{Sent}_t^{\perp}$			0.001			
			(0.23)			
TRA × $\text{Sent}_t^{\perp}$			0.001			
			(0.37)			
Constant	0.373***	0.373***	0.374***	0.322***	0.320***	0.322***
	(55.75)	(55.77)	(54.24)	(32.09)	(31.38)	(30.00)
Observations	133452	133452	138162	163446	156981	160258
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Qtr-of-yr FE	Yes	Yes	Yes	Yes	Yes	Yes
Horizon and TO	Yes	Yes	No	No	Yes	No
Strategy	No	No	Yes	No	No	Yes

Table A10: Lagged market sentiment and uncertainty

The table provides results of regressions of quarterly PWR on the average orthogonlaized market sentiment and VIX during the previous quarter. Sentiment is interacted with dummy variables that identify investors by investment horizon through average portfolio duration, trading intensity through quarterly prtfolio turnover (TO), and general investment strategy from Bushee (1998). All regressions control for the volatility of PWR, portfolio MA, exposure to FF-3 factor portfolios, investor characteristics, and seasonality via quarter-of-year fixed effects. Standard errors are multi-way clustered along quarter and investor, and t-statistics are presented in parentheses. ***, **, and * indicate that the parameter estimate is significantly different from zero at the 1%, 5%, and 10% level, respectively. The sample spans from 1995 to 2019, and covers all quarterly portfolio holdings of institutional investors for which a minimum of 8 observations are available. All variables are described in Table 1.

	Sentiment$^{\perp}$ (lagged)			VIX (lagged)		
	(1)	(2)	(3)	(4)	(5)	(6)
$\text{Sent}^{\perp}_{t-1}$	0.008***	0.008***	0.008**			
	(4.90)	(4.17)	(2.89)			
$\varnothing\text{VIX}_{t-1}$				0.003***	0.003***	0.003***
				(4.75)	(4.74)	(4.73)
$\varnothing\text{VIX}^2_{t-1}$				-0.000***	-0.000***	-0.000***
				(-4.72)	(-4.67)	(-4.69)
Short-term × $\text{Sent}^{\perp}_{t-1}$	-0.005***					
	(-3.97)					
Long-term × $\text{Sent}^{\perp}_{t-1}$	0.001					
	(0.78)					
Low TO × $\text{Sent}^{\perp}_{t-1}$		0.003*				
		(2.34)				
High TO × $\text{Sent}^{\perp}_{t-1}$		-0.003**				
		(-2.99)				
Dedicated × $\text{Sent}^{\perp}_{t-1}$			0.001			
			(0.13)			
Transient × $\text{Sent}^{\perp}_{t-1}$			0.001			
			(0.76)			
Constant	0.374***	0.374***	0.375***	0.323***	0.321***	0.324***
	(57.52)	(57.59)	(56.29)	(31.65)	(30.97)	(29.87)
Observations	132,692	132,692	137,367	162,649	156,221	159,463
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Qtr-of-yr FE	Yes	Yes	Yes	Yes	Yes	Yes
Horizon and TO	Yes	Yes	No	No	Yes	No
Strategy	No	No	Yes	No	No	Yes

Low-carbon mutual funds*

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Abstract

Low-carbon mutual funds allow investors to purchase lower exposure to climate change risk at the cost of reduced sectoral diversification. The effects are sizable, as seen by comparing funds receiving Morningstar's "Low Carbon Designation" (LCD) with conventional funds. On balance, this proposition proves to be appealing for investors. Low-carbon funds experience strong additional flows after the introduction of the LCD and subsequent updates. Active funds that missed the label at its initial release later shifted their holdings towards less carbon-intensive firms. These findings suggest that intermediaries use climate performance to compete for investment flows and that this competition can significantly alter the risk profile that mutual fund investors obtain.

JEL Classification: D03, G02, G12, G23
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1 Introduction

Climate change is one of the key economic challenges of our time. Economists and public policy scholars increasingly agree on the merits of carbon taxes and/or tradable permits to ensure adequate pricing of carbon emissions at the international level.[1] However, given the current practical and political challenges in implementing such policies, policy-makers are also exploring alternative strategies to accelerate the transition to a low-carbon economy. One central approach is to make "financial flows consistent with a pathway towards low greenhouse gas emissions" (Paris Agreement, Article 2) by improving the climate-related information available to investors about their portfolios.[2]

The success of this strategy, however, relies on the twin assumptions that investors will respond to more transparency by demanding more climate-conscious products and that financial intermediaries will in turn shift their assets towards more climate-friendly holdings. However, the triggering of this virtuous circle is far from obvious, because low-carbon funds are likely to have both benefits and costs. They can provide investors with a channel to reduce their exposure to climate risks, but at the expense of a lower sectoral diversifica-

[1]See Nordhaus (2019). On the internalization of external costs in general see the fundamental contributions of Pigou (1920), Coase (1960), and Weitzman (1974).

[2]For instance, as a follow-up to the "Action plan for sustainable finance" of March 2018 (European Commission, 2018), in November 2020, European legislators adopted the "Regulation on sustainability-related disclosures in the financial services sector", which came into force in March 2021 (European Parliament and Council, 2020). It contains various provisions aimed at "reducing information asymmetries in principal-agent relationships with regard to the integration of sustainability risks, the consideration of adverse sustainability impacts, the promotion of environmental or social characteristics, and sustainable investment". Regulators are also currently developing a proposal for a EU-wide eco-label for financial products to help retail investors express their investment preferences on sustainable activities.

tion relative to the market portfolio, at least in the short-term. This paper quantifies that trade-off and then studies how investors and fund managers respond to it.

Mutual funds play a crucial role in the overall economy. As of year-end 2018, US and European mutual funds, respectively, had some USD 17.7 trillion and USD 11 trillion in assets under management (Investment Company Institute, 2019). On April 30, 2018, Morningstar, the most important information provider in the mutual fund industry, introduced an eco-label for mutual funds, the Low Carbon Designation (LCD). This event increased the level and salience of information available to investors on the climate performance of mutual funds.

After explaining the institutional setting in Section 2 and describing the data in Section 3, in Section 4 we show that low-carbon funds have a specific risk profile compared to conventional and also more generic sustainability funds. While this result qualitatively follows naturally from low-carbon funds' under-weighting of high-carbon sectors, the quantitative effects are non-obvious ex ante.

The differences among funds are sizable. Specifically, low-carbon funds strongly outperform conventional funds in months with higher salience of climate change risks, as proxied by the negative climate news index used in Engle et al. (2020). LCD funds on average load three quarters of a standard deviation less on negative climate news than not-LCD funds.

However, low-carbon funds also display substantially lower diversification. LCD funds exhibit 14% higher idiosyncratic risk than not-LCD funds. Indeed, low-carbon funds have quite low "balance" (Pástor et al., 2020a) with respect to the current market portfolio (that is, a market portfolio of a still not-low-carbon economy). These results are particularly relevant considering that diversification is one of the main *raisons d'être* and advantages of mutual funds in the first place. Whether investors are willing to give up diversification opportunities in order to invest low-carbon is far from obvious, and hence worth studying.

Importantly, we show that investors do not face such a trade-off between avoiding climate change risk risk and diversifying their portfolios when dealing with the "Globes", the other (more generic) sustainability ratings made salient by Morningstar (Ammann et al., 2018; Hartzmark and Sussman, 2019).

Next, in Section 5 we exploit the quasi-experimental setting of the introduction of the LCD to learn about investor preferences regarding "climate-friendly" funds, as captured by fund flows. The existence of the above trade-off between two types of risks makes the fund-flows effects of the LCD ex-ante unclear and significantly less obvious than the effects of generic ESG ratings already documented in the extant literature. We find that funds that were labeled as low-carbon at the end of April 2018 enjoyed a substantial increase in their monthly net flows relative to conventional funds, net of the effect of other fund characteristics. The economic impact is large. It corresponds to the effect of about 47% of a one-standard deviation stronger financial performance in the prior month. The effect is even stronger for European funds.

These findings hold controlling for many other factors, including the generic ratings for fund performance ("Stars") and sustainability ("Globes") of Morningstar for which prior work had shown an impact on fund flows (e.g., Del Guercio and Tkac, 2008, Ammann et al., 2018, Ben-David et al., 2019, Hartzmark and Sussman, 2019, and Evans and Sun, 2021). A battery of robustness checks alleviate concerns that the findings are driven by other unobserved factors.

The boost in flows received by low-carbon funds is not a one-off event: Receiving (losing) the LCD in quarterly updates that followed the initial publication through September 2019 translates into positive (negative) flow effects that are comparable to those at the initial introduction.

Finally, Section 6 studies how mutual funds actively changed their portfolios after the initial release of the LCD and the clear revelation of investors' preference for low-carbon investment products. We find that between April 2018 and September 2019, active funds rebalanced their portfolios towards more climate-conscious firms. For example, during the six quarters the LCD was in place through September 2019, mutual funds that were not considered low-carbon in April 2018 reduced their portfolio Carbon Risk (the portfolio's exposure to firms with un-managed climate-risks) by 17% of a standard deviation relative to LCD-recipients. We obtain similar results when accounting for changes in the underlying relative asset valuations of carbon-intensive sectors.

This "green shift" of mutual fund portfolios in recent years is likely influenced by several factors. We interpret the observed behavior of fund managers as a supply-side reaction to a general increase in demand for low-carbon investment products and higher awareness of climate-related risks, accelerated in the mutual fund industry by the release of Morningstar's LCD. Our setting is particularly suited to capture the effects of such competitive behavior because it allows us to study how funds' climate performance evolved after it became publicly available and proved an important driver of fund flows.

Our paper contributes, first, by empirically documenting the potential benefits and costs of low-carbon investment products. Existing research suggests that firms with better environmental performance have lower exposure to climate-related risks, and are hence priced accordingly by financial markets (e.g., Bolton and Kacperczyk, 2020, 2021; Engle et al., 2020; Ilhan et al., 2021; Huynh and Xia, 2020). Our analyses confirm that this type of insurance property extends to mutual funds under-weighting carbon-intensive firms. This benefit, however, comes at the expense of a lower sectoral diversification, which limits risk-sharing from a traditional portfolio-theory perspective (Markowitz, 1952). The trade-off that we highlight is consistent with the theoretical literature on green investing (Heinkel et al., 2001; Pástor et al., 2020b; Pedersen et al., 2020), but is still empirically under-explored. Given the growing expectations on finance to support the decarbonization of the economy, both policy-makers and investors should carefully weigh the benefits and costs of reducing investment flows to specific sectors that are still part of the economy.

Second, we complement the literature on investor behavior, in particular on whether and why investors prefer socially responsible investment products (e.g., Anderson and Robinson, 2019; Barber et al., 2020; Bassen et al., 2018; Bauer et al., 2018; Bialkowski and Starks, 2016;

Bollen, 2007; Bonnefon et al., 2019; Geczy et al., 2021; Renneboog et al., 2011; Riedl and Smeets, 2017).[3] The natural experiment that we analyze is appealing in this respect. Before the introduction of the LCD, investors already had the chance to self-select into different funds on the base of their generic sustainability preferences, given the availability since 2016 of easy-to-process information about the ESG performance of funds (Hartzmark and Sussman, 2019).[4] Hence, the effect that we identify can be attributed to investors' preferences for climate-related features, net of their preferences for sustainability more broadly defined. In addition, the empirical setting allows us to document that many investors prefer low-carbon funds despite having to give up diversification opportunities. In this perspective, our paper also relates to recent research studying the drivers of investor demand for high idiosyncratic volatility funds and the related tradeoffs (Goetzmann and Kumar, 2008; Clifford et al., 2020; Pástor et al., 2020a).

Third, we complement the literature that studies the behavior of professional money managers. Important prior studies in this area include Berk and Green (2004), Berk and Van Binsbergen (2015), Chevalier and Ellison (1997), Cooper et al. (2005), Donaldson and Piacentino (2018), Guercio and Reuter (2014), Harris et al. (2015), Hortaçsu and Syverson (2004), Kempf and Ruenzi (2008), and Wahal and Wang (2011). Most studies consider mu-

[3] A broader stream of research studies the preferences of investors for socially and environmentally responsible firms, primarily through the lens of stock prices (e.g. Hong and Kacperczyk, 2009; Hong and Kostovetsky, 2012; Krüger, 2015; Lins et al., 2017; Flammer, 2021) or through the portfolio holdings of institutional investors (e.g, Dyck et al., 2019; Fernando et al., 2017; Gibson and Krüger, 2020; Gibson et al., 2019; Krüger et al., 2020) or both (Ramelli et al., 2021).

[4] More recently, Pástor and Vorsatz (2020) and Döttling and Kim (2020) study the effects of mutual funds' sustainability Globe ratings on fund flows during the COVID-19 crash.

tual fund manager behavior as a function of traditional performance metrics such as fees and returns. However, in recent years, ESG factors (in particular related to climate change) have gained increasing importance in shaping the asset management industry. For instance, Krüger et al. (2020) and Ilhan et al. (2020) provide survey evidence on the importance of climate risks for institutional investors. As deeds tend to speak louder than words, an investigation of how mutual funds actually adjust their holdings to newly released information on the climate risk of their portfolios is needed. This is one of the results that this paper delivers.[5]

2 Empirical setting

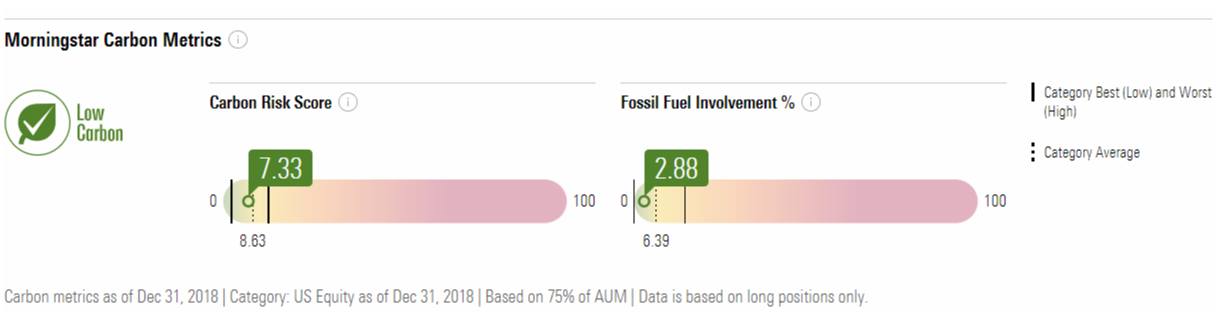
On April 30, 2018, Morningstar introduced the "Low Carbon Designation" (LCD) for mutual funds. This label is depicted as a green leaf icon which is visible on the fund's report, as shown in Figure 1. While not the first type of sustainability evaluation for funds, the LCD is particularly interesting because it specifically aims at helping clients to easily identify mutual funds with portfolios aligned with the transition to a low-carbon economy.

Details on the methodology underlying the assignment of the LCD are in Morningstar

[5]Alok et al. (2020) examine how fund managers change their holdings after they *experience* large climatic disasters, that is, after specific realizations of climate risk. More recently, Choi et al. (2021) document a decrease in institutional investors' exposure to domestic carbon-intensive firms after 2015, especially in countries with high climate awareness. Our analyses at the mutual fund level around a specific event indicate that, even in recent years, increased transparency on climate-related risks in the asset management industry is a significant driver of this global carbon divestment trend.

(2018a,b).[6] To receive the LCD, a mutual fund has to comply with two criteria: (1) a 12-month trailing average "Portfolio Carbon Risk Score" below 10 (out of 100); and (2) a 12-month trailing average "Fossil Fuel Involvement" below 7%. The Portfolio Carbon Risk Score is calculated if more than 67% of a fund's portfolio assets (based on the combined market value of bond and equity holdings) have a carbon-risk rating from the ESG research provider Sustainalytics.

Figure 1: Morningstar Direct snapshot



The portfolio scores are based on *issuer-level* variables from Sustainalytics, which are updated on a yearly frequency. According to Sustainalytics, the "Carbon Risk Score" quantifies the portfolio companies' exposure and management of material carbon issues in their operations as well as their products and services (Morningstar, 2018b). The management of carbon issues focuses on portfolio companies' preparedness and track record in managing these issues. In Table A1 in the Appendix, we provide summary statistics of firm-level

[6] For the purpose of our empirical analysis, we take Morningstar's approach to the assessment of funds' climate-related performance as given. Our objective is neither to praise nor criticise Morningstar's methodology, but rather to exploit it to study the behavior of both mutual fund clients and mutual fund managers.

Carbon Risk scores by industries. As expected, firms in high-emitting sectors (e.g., Energy, Materials, and Utilities) are considered those having the highest carbon risks. However, within all sectors, there is substantial variability of this measure.

Morningstar computes the fund-level Carbon Risk scores by weighting the firm-level scores by the total investment (debt and equity) that a mutual fund holds at the end of the quarter in a given company.[7] As of April 2018, having a Carbon Risk score below 10 implies being amongst the 29% of funds with the best performance on this dimension.

"Fossil Fuel Involvement" measures the percentage of portfolio firms that derive a significant share of revenues from activities related to fossil fuels, including thermal coal, oil and gas, oil sands, shale energy, deep-water production, and Arctic offshore exploration. As of April 2018, having a 12-months trailing average Fossil Fuel Involvement below 7% represents a 33% under-weighting of fossil fuel-related companies relative to the global equity universe.

The LCDs were released for the first time at the end of April 2018 and assigned to funds based on their carbon scores as of the end of March 2018. Responding to our clarifying questions, Morningstar representatives noted that they did not communicate in advance the release of the label to either mutual fund managers or their clients. Indeed, the analysis of pre-publication trends further below is in line with the release of the LCD being unexpected.

[7] Chen et al. (2021) argue that many managers of fixed-income mutual funds misreport the credit quality of their assets to Morningstar to influence its assessments, in particular the Stars ratings. Contrary to the credit quality of fixed-income assets, the measures underlying the LCD (portfolio carbon risk and portfolio fossil fuel involvement) are not self-reported by fund managers, but are instead computed by Morningstar based on funds' portfolio holdings. Of course, we cannot definitively exclude that some funds decide to misreport their holdings. However, significant legal and reputational risks are associated with such misreporting. Overall, therefore, misrepresentation does not seem to be a major concern in our setting.

The LCDs for the period from January through the end of April 2018 (pre-publication period) were also released at the end of April 2018, based on the holdings in the previous quarters. Morningstar updates the portfolio aggregates of carbon risk metrics on a quarterly basis, and changes the LCD label assignment accordingly. This setting allows us to study not only the effects of the initial LCD release, but also the effects of later changes.

3 Data

We obtain survivorship-bias-free data (in USD) for all open-end mutual funds domiciled in Europe and USA from Morningstar Direct. To work with a relatively homogeneous sample, we drop all funds classified by Morningstar in categories that are pure fixed income, sector-specific, or investing exclusively outside US and Europe.[8] We remain with 20 categories composed of equity and diversified funds.[9]

Our sample period spans April 2017 (one year before the LCD introduction) through September 2019. Mutual funds issue several share classes to target specific investors groups or geographies. However, the underlying portfolio and, therefore, the LCD, is the same across share classes. Consequently, all our analyses are conducted at the fund level.[10]

[8] Our results hold also when using the full sample of funds domiciled in Europe and USA.

[9] Specifically, the categories in our sample are: Aggressive Allocation, Allocation Miscellaneous, Cautious Allocation, Equity Miscellaneous, Europe Emerging Markets Equity, Europe Equity Large Cap, Flexible Allocation, Global Equity Large Cap, Global Equity Mid/Small Cap, Long/Short Equity, Moderate Allocation, Target Date, UK Equity Large Cap, UK Equity Mid/Small Cap, US Equity Large Cap Blend, US Equity Large Cap Growth, US Equity Large Cap Value, US Equity Mid Cap, US Equity Small Cap, and Europe Equity Mid/Small Cap.

[10] Our fund-flows results continue to hold when using data at the share-class-level (which allows, for

In aggregating data from the share-class to the fund level, we compute funds' returns and volatility as value-weighted average values across different share classes. Fund assets (in USD) is the sum of the assets under management of a fund in its different share classes. Other fund-level information (including the assignment of the LCD) is retrieved from the largest share class of the funds. Funds with more than 50% of assets in institutional share classes are classified as institutional funds.[11]

Following Sirri and Tufano (1998), flows are computed as the monthly growth of assets under management net of reinvested returns. To ensure the robustness of our analysis, we trim flows at the 1st and 99th percentiles. Moreover, we compute a measure of normalized flows following Hartzmark and Sussman (2019): First, we split the sample into deciles according to fund size. Second, we rank funds according to their net flows within their size decile and compute percentiles of the net flow rankings. These percentiles correspond to the normalized flows variable.

Throughout the paper, returns are expressed in percentage points. Our main measure of returns is the total monthly return as reported by Morningstar. To obtain a relative measure of returns, we adjusted these for the assets-weighted averages by Morningstar categories (as

example, for different flows for different share classes), and clustering standard errors at the fund level. For the results on fund responses, no such robustness check can be conducted because all relevant variables only vary on the fund level.

[11]Morningstar classifies as institutional the share classes that meet one of the following criteria: have the word "institutional" in the name; have a minimum initial purchase of USD 100,000 or more; specifically address institutional investors or those purchasing on a fiduciary basis, as stated in the fund prospectus. We define a fund as institutional when more than 50% of assets in share classes are dedicated to institutional clients.

done, for instance, by Pástor et al., 2017). We also compute CAPM-adjusted and Fama-French-adjusted returns using betas estimate through OLS regressions of monthly data from December 2016 through April 2018.

We compute the return volatility as the standard deviation of returns using a 12-month rolling window. We also collect information on the net expense ratio reported in the latest prospectus, age, global category (capturing the investment style), Morningstar's overall rating (the Morningstar "Stars", on a 1-5 scale, with 5 to indicate top financial performers), whether the fund is classified as "socially conscious",[12] and its overall sustainability ratings (the Morningstar "Globes", on a 1-5 scale, with 5 to indicate top sustainability performers).

To account for the impact that "Stars" have on fund flows (Del Guercio and Tkac, 2008), we define the variable ΔStars indicating funds that experienced an upgrade or a downgrade in the "Star" rating from the previous month, considering observations with continuing missing Stars ratings as no change. Similarly, to account for the impact of the generic sustainability rating (Ammann et al., 2018; Hartzmark and Sussman, 2019), we define the variables Δ1 Globe and Δ5 Globes as the monthly changes of dummy variables indicating funds in the two extreme sustainability categories (1 Globe and 5 Globes), considering the observations with continuing missing sustainability ratings as no change.

- Table 1 -

[12] Morningstar classifies as socially conscious any fund that identifies itself as investing according to some non-economic guidelines, for instance by excluding certain sectors or companies from the investable universe, or by aiming at selectively investing in good-performing companies based on environmental and social criteria.

Panel A of Table 1 shows summary statistics for fund-month observations from April 2017 through September 2019 for which information of flows and LCD is available. Panel B provides a snapshot of the statistics as of the end of April 2018. The sample covers some 13,500 funds, of which around 18% obtained the Low Carbon Designation. The mean net flows in our sample period are negative, partially reflecting the overall shift of mutual fund clients towards index funds and ETFs. The average annual expense ratio is about 1.1 percentage points.[13] 10% of funds self-classify themselves as socially conscious. Interestingly, from the population of socially conscious funds, only a third received the LCD. Around a quarter of all funds are primarily sold to institutional clients. Appendix Table A2 shows the correlations between the variables in our main sample. On average, low-carbon-designated funds have higher assets under management, volatility, and expense ratios.

- Table 2 -

Table 2 shows the geographical distribution of the sample as of the end of April 2018. Around 9,300 funds are domiciled in Europe, and 4,200 in the USA. The share of funds that received the initial Low Carbon Designation is 18% in Europe and 17% in the USA.

[13] Information on this variable is missing for most of the sample as its annual reporting is compulsory only in the USA. In order not to significantly restrict our European sample, we do not include this variable in our main regressions, but our findings hold even when we do.

4 The risk profile of low-carbon funds

This section considers the potential risk benefits and costs of investing in low-carbon funds, compared to conventional funds and more generic sustainability funds.

To motivate why low-carbon funds may have specific financial characteristics, Table 3 shows the percentage of low-carbon funds for different values of Morningstars' sustainability ratings ("Globes") and overall performance ratings ("Stars"). Funds with high "Globes" and "Stars" ratings are more likely to receive the LCD. However, funds can be considered low-carbon despite having only one or two Globes, or one or two Stars. These relatively low correlations confirm that the climate-specific label we study is substantially different from other ratings already available on Morningstar.

- Table 3 -

4.1 Exposure to climate change risks

Given the emphasis of the existing literature on green investing's risk-management properties (e.g., Bolton and Kacperczyk, 2020; Engle et al., 2020; Ilhan et al., 2021; Pástor et al., 2020b), we start by analyzing the claimed ability of low-carbon funds to hedge future realizations of climate change risks.

The risks posed by climate change are unconventional and non-normal, with long-term and "fat tail" properties (Weitzman, 2009, 2011). These risks have still to materialize in their full potential, both in terms of natural disasters and regulatory measures. They are, therefore, difficult to quantify based on past realized returns.[14] However, one can get a sense of the benefits of low-carbon funds in insuring against climate change by gauging the sensitivity of these funds' performance to variations in the perception of climate risk.

Therefore, we compute individual funds' factor loading on negative climate change news. Specifically, we regress each US fund's monthly returns on the three Fama-French global factors (obtained from Kenneth French's website) and the news-based climate change risk index from Engle et al. (2020), standardized to have zero mean and unit standard deviation.[15] We base our estimation on the 17-month period from December 2016 through April 2018, with a minimum of 12 monthly return observations, and we winsorize the estimated loadings at the 1st and 99th percentiles.[16] The estimated coefficient on the news-based climate change risk index represents the fund-specific sensitivity to negative climate-related information

[14]The finance literature on rare disasters shows how some "puzzles" in finance (e.g., excess volatility and high equity premiums) can be rationalized as the pricing-in of tail risks of future disaster events (e.g., Gabaix, 2012; Wachter, 2013; Tsai and Wachter, 2015). When dealing with fat-tail risks, the distribution of realized returns can be only partially informative of actual expected returns (Elton, 1999).

[15]Engle et al. (2020) find that environmentally-responsible firms – based on Sustainalytics' environmental scores – outperform non-environmentally-responsible firms in months with more climate-related news. For our analysis, we use the negative news-based risk index the authors obtained from the data analytics provider Crimson Hexagon (CH) ("CH Negative Climate Change News Index"), which focuses exclusively on negative climate news, and is available from January 2008 through May 2018. We thank Stefano Giglio and Johannes Stroebel for making these data available on their websites. We here restrict our attention to US funds for consistency with the Engle et al. (2020) index.

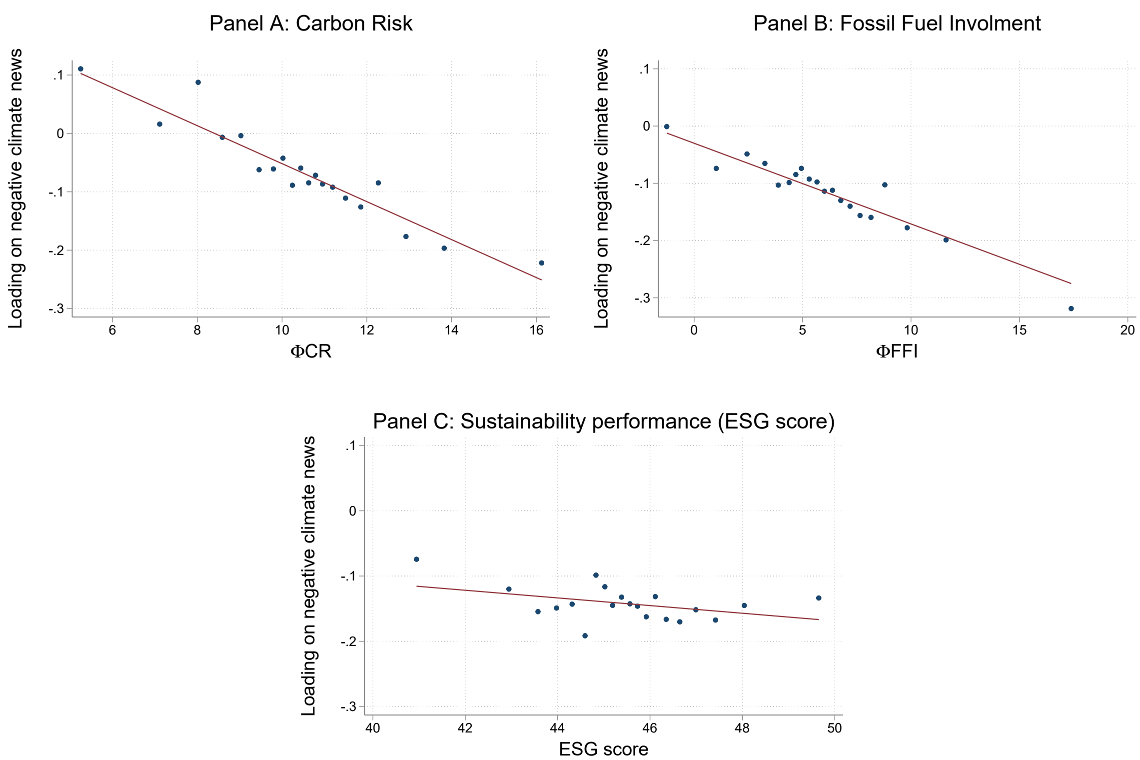
[16]There are three advantages of using a relative short estimation window in this application. First, this better captures the sensitivity of assets to the fast-evolving concerns of investors on climate change, as also discussed by Huynh and Xia (2020), who use a similar approach to study the effects of firms' past loading on climate news on corporate bond pricing. Second, it mitigates concerns over portfolio changes over time, as the LCD criteria disclosed in May 2018 (CR and FFI) reflect funds' average portfolio compositions only over the previous 12 months. Third, it allows us to focus on the period following the 2016 election of Donald Trump in November 2016, which caused high negative attention to climate change and, at least in the short run, an out-performance of carbon-intensive sectors (Ramelli et al., 2021).

(akin to a "climate beta"), net of the sensitivity to the market, size, and value factors. Since the climate beta is computed from relatively small changes in negative climate change news, it arguably provides a lower-bound estimate of a fund's exposure to future climate risks, which are likely to follow non-normal distributions.

Figure 2 shows in binned scatter plots how the funds' loadings on negative climate news relate to carbon risk (Panel A), fossil fuel involvement (Panel B), and generic sustainability scores (Panel C), controlling for category fixed effects and fund size.

We observe that funds with lower CR and FFI have a significantly ($p < 0.001$) less negative loading on climate news, i.e., they tend to outperform when the "negative climate news" factor hits. Specifically, LCD funds have an average loading on negative climate news that is 0.248 higher than not-LCD funds (0.084 vs -0.164, $p < 0.001$), equal to approximately three quarters of the standard deviation of the loading (0.33), a sizable difference.

Figure 2: LCD and loading on negative climate news
These figures show binned scatter plots of US funds' loading on negative climate news (climate beta) against funds' 12-month moving average Carbon Risk (Panel A), funds' 12-month moving average Fossil Fuel Involvement (Panel B), and generic sustainability performance (Panel C), controlling for category fixed effects and log assets. The sample is composed of US mutual funds as of April 2018. The loading on climate news is the coefficient on the standardized negative news-based climate risk index used in Engle et al. (2020) when regressing, for each fund, the monthly returns from December 2016 through April 2018 on that index and the Fama-French three global factors.



Critically, as illustrated in Panel C, we do not identify any relation between the loading on climate news and the generic sustainability score ($p = 0.15$). The same relation holds when considering the Globes ratings, which are allocated on the basis of the relative ranking in sustainability score within each category (see Panel A in Figure A1 in the Supplementary Appendix).

In sum, this evidence confirms that the release of the LCD provided investors with a valuable new proxy of a fund's exposure to future realizations of climate change risks.

4.2 Exposure to diversifiable risks

Are the benefits of low-carbon funds a "free lunch", or do they come at the cost of some sacrifices? We expect a major cost of low-carbon investing to be missed diversification opportunities, as long as the overall economy has not reached the low-carbon state, that is, as long as carbon-intensive companies are major constituents of the market portfolio.

To quantify this cost, we compute each fund's idiosyncratic volatility, a widely used measure of funds' realized diversifiable risk. Following the common practice in the literature, we define idiosyncratic volatility as the standard deviation of monthly residuals from a Fama-French three-factor model regression (e.g., Goyal and Santa-Clara, 2003; Bali et al., 2005; Ang et al., 2006, 2009; Huang et al., 2010). We again focus on the period from December 2016 through April 2018, before the publication of the LCD, with at least 12 observations of monthly returns.[17] From the same regressions, we also obtain individual funds' alpha

[17] To estimate the fund-specific Fama-French three-factor model, we obtain the market, size, and value factors for from Kenneth French's website. We use US-specific factors for US funds and Europe-specific factors for European funds. However, similar results are obtained when using the global factors for all funds. Evans and Sun (2021) provide evidence on the power of the Fama-French three-factor model in explaining funds' flow-return sensitivity.

relative to the Fama-French three-factor model.[18]

In Table 4, we run cross-sectional regressions of funds' idiosyncratic risk on decile indicators for the two performance scores underlying the LCD – carbon risk (CR) (column (1)) and fossil fuel involvement (FFI) (column (2)) – and the ESG score underlying the Globes rating (column 3)). The regressions use the fifth decile as the baseline and control for funds' log assets, alpha, and category. (Similar results are obtained when also controlling for fund age and activeness.)

- Table 4 -

The estimates in columns (1) and (2) show that funds in the first and second deciles of CR and FFI (i.e., funds with a strong tilt towards low-carbon firms) display a *higher* idiosyncratic risk than funds with climate metrics closer to the median values. Indeed, LCD funds – on average falling in the second decile of CR and the third decile of FFI – have a mean idiosyncratic risk of 1.70%, about 14% higher than the mean of 1.49% for not-LCD funds.

Naturally, *over-weighting* carbon-intensive sectors also increases idiosyncratic risk, as indicated by the coefficients on the highest deciles of CR and FFI. By definition, idiosyncratic

[18] As shown in Table A3, low-carbon funds, on average, exhibit higher alphas than other funds, and it is therefore important to control for realized performance when comparing idiosyncratic risk. However, given our short sample period, one should not necessarily consider the observed out-performance of low-carbon funds as a compensation for higher idiosyncratic risk. Indeed, the evidence on the relation between idiosyncratic volatility and future expected returns is mixed (Ang et al., 2006, 2009; Huang et al., 2010). The model in Pástor et al. (2020b) suggests that while green assets have lower expected returns in equilibrium, they can experience higher realized returns after changes in investor 'green' preferences.

volatility is minimized by the market portfolio, which has values of CR and FFI above the LCD thresholds, as the two LCD criteria were set to reward funds with better-than-average climate performance. Either under- or over-weighting high-carbon firms relative to the market increases volatility.

Importantly, higher idiosyncratic risk is not necessarily a common feature of all sustainable investing strategies: In column (3) of Table 4, we observe that funds falling in the highest deciles of ESG scores do not display higher idiosyncratic risk. By contrast, low-sustainability funds (those in the bottom four deciles of ESG score) do have a significantly higher idiosyncratic risk than median-sustainability funds.[19] Naturally, the same result obtains when using the Globes ratings (as illustrated in Panel B of Figure A1 in the Appendix).

[19]This result is consistent with Renneboog et al. (2008) who document lower idiosyncratic risks for socially responsible investments funds and with Maxfield and Wang (2020), who show that funds with higher Morningstar sustainability scores have lower idiosyncratic risk. More generally, the finding is in line with the idea that sustainable investing can help investors avoid companies with higher firm-specific risks (Godfrey et al., 2009).

Figure 3: LCD criteria and idiosyncratic risk
These figures show binned scatter plots of funds' idiosyncratic risk against 12-month average Carbon Risk (Panel A), 12-month average Fossil Fuel Involvement (Panel B), and ESG score (Panel C), controlling for category fixed effects and log assets. *Idiosyncratic risk* is the standard deviation of monthly residuals relative to Fama-French three-factor model regressions run over the period from December 2016 through April 2018. For illustrative purposes, in the figure we winsorize CR and FFI at the 1st and 99th percentiles.

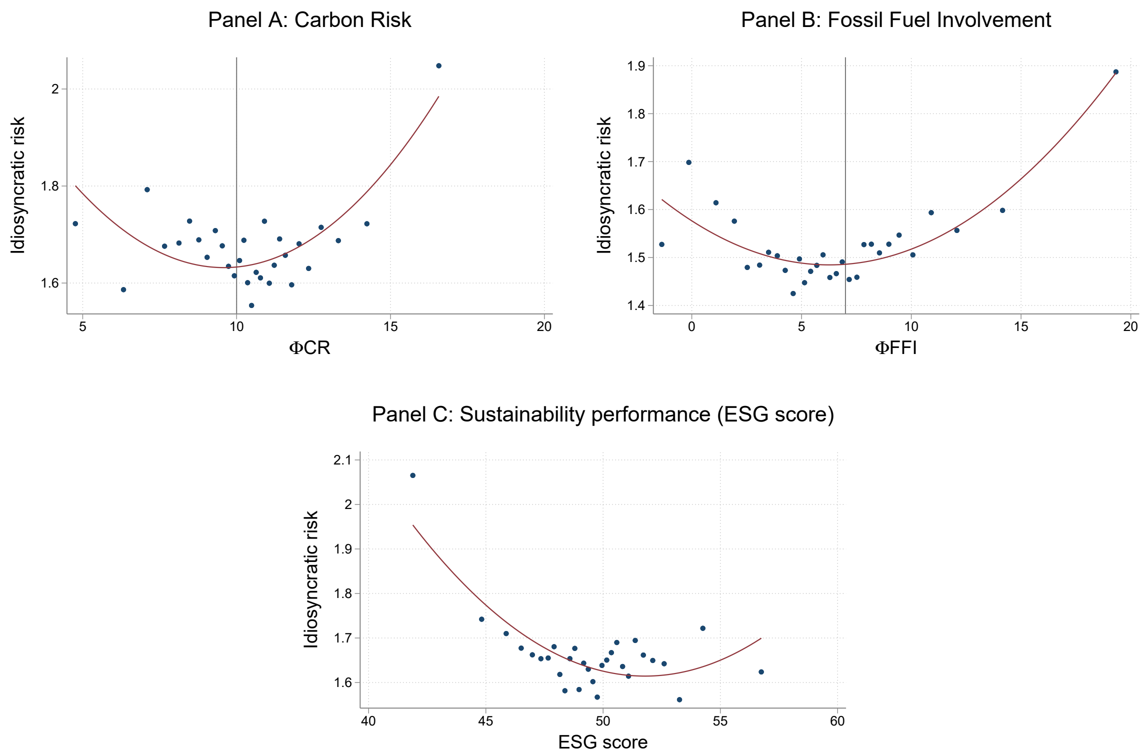


Figure 3 illustrates in binned scatter plots the relation between idiosyncratic risk and the three sustainability metrics under review: CR (Panel A), FFI (Panel B), and ESG score (Panel C). The decision to invest in a low-carbon rather than in a "average-carbon" fund implies accepting (intentionally or not) higher diversifiable volatility. The decision to invest in a high-ESG rather than an average-ESG fund appears more innocuous in this respect.

The contrasting effects of the Morningstar Globes and the LCD on idiosyncratic volatility are due to crucial differences in their scope and methodology: While Morningstar assigns the Globes based on "best-in-class" ESG sustainability scores, the LCD is granted to funds that under-weight carbon-intensive sectors and firms. In other words, the higher volatility of LCD funds emerges as a natural by-product of a smaller sectoral diversification, which limits risk-sharing from a mean-variance perspective (Markowitz, 1952).[20]

Overall, the analyses presented in this section establish a special profile of low-carbon funds, different from both conventional and high-sustainability funds. Specifically, low-carbon funds can provide investors with a channel to potentially reduce their exposure to realizations of climate change risks, in addition to satisfying preferences for green investing. However, these benefits come at the expense of a lower (sectoral) diversification. In other words, with low-carbon funds easily identifiable, investors face a trade-off between minimizing idiosyncratic risk given the current state of the market portfolio and investing consistently with a low-carbon economy.[21] How investors and fund managers respond to this fundamental

[20]To probe this interpretation, we employ data from Pástor et al. (2020a). These authors decompose portfolio diversification in terms of resemblance of portfolio weights relative to the market cap weights ("balance") and number of stocks held ("coverage"). By matching our dataset with the data used in Pástor et al. (2020a), we remain with 915 US domestic equity mutual funds with available diversification data for 2014. Results available on request show that funds classified as low-carbon in April 2018 have a statistically significant lower "balance", even after controlling for category fixed effects. By contrast, the number of Globes is unrelated to "balance." Low-carbon funds also display a lower "coverage" than other funds, but the difference is not statistically significant when accounting for category fixed effects. We thank Lucian Taylor for making these data available on his website and for suggesting this analysis.

[21]The theoretical literature of responsible investing recognizes the existence of such trade-off. Pástor et al. (2020b), for instance, show that the propensity of climate-conscious investors to invest in green investment products is inversely related to their risk aversion, as moving away from the market portfolios comes at the cost of lower diversification. Of course, green investing can come in different degrees and shapes. For instance, Andersson et al. (2016) argue that a sector-by-sector ESG filtering approach can allow investors to

trade-off is ex-ante unclear. This open question motivates the analysis in the following section.

5 Investor responses

This section explores the initial reaction of mutual funds investors to the Low Carbon Designation (LCD). It is possible that investors by and large do not care for the climate performance of mutual funds or already had other means to express their potential carbon-related preferences. Thus, the null hypothesis is no effect on fund flows after the introduction of the LCD. Alternatively, if investors are eager to invest in climate-friendly mutual funds despite the lower diversification these funds entail relative to the market portfolio, we expect funds that Morningstar labeled as low-carbon to experience abnormally high flows after April 2018.[22] Yet alternatively, if investors anticipate too large drawbacks from the lack of diversification, they might even (relatively) reduce flows to LCD finds.[23]

significantly reduce carbon risk at the cost of a small tracking error with respect to the benchmark index.

[22]Kacperczyk et al. (2005) show that a higher sectoral concentration can be beneficial for investors if fund managers have informational advantages in specific industries. In this respect, it may even be possible that some investors perceive the lower diversification of low-carbon funds as indicative of superior "skills" of fund managers, at least with respect to climate issues, which could manifest themselves in terms of either picking the right stocks or timing the market-wide transition to a low-carbon economy (Kacperczyk et al., 2014). Our empirical tests account for fund managers' demonstrated skills by controlling for a fund's Stars ratings and past realized returns.

[23]A caveat for analyses like ours is that we can not observe investors' full holdings and how they changed after entering an LCD fund. An investor strongly exposed to high-carbon firms may even increase diversification by re-directing capital to a low-carbon fund. What we emphasize is the diversification opportunity an average investor misses when choosing a low-carbon funds instead of more balanced available options. Particularly for retail investors it is reasonable to expect this choice to also affect their overall portfolios, considering the low number of funds such investors use (e.g., Huberman and Jiang, 2006).

We start this section by graphically depicting flows for low-carbon and not-low-carbon funds. We then formally test whether investors reward low-carbon funds.

5.1 Graphical evidence

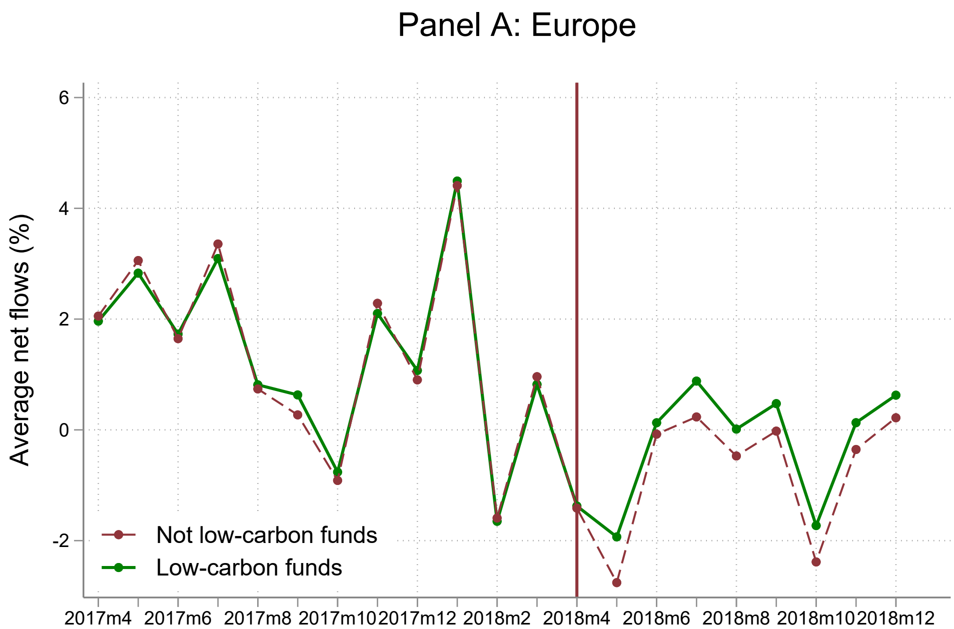
Figure 4 illustrates the average equally-weighted monthly net flows of funds that were categorized as low-carbon at the end of April 2018 and into or out of funds that did not (not-low-carbon), from April 2017 through December 2018. Importantly, information about the LCD became available to investors only from the beginning of May 2018. We call the period April 2017 through April 2018 the pre-publication period. For now, we focus on the post-publication period through December 2018 to document the initial reshuffling of flows caused by the release of the LCD. Section 5.3 investigates the fund-flow effects of LCD upgrades and downgrades over an extended sample period through September 2019.

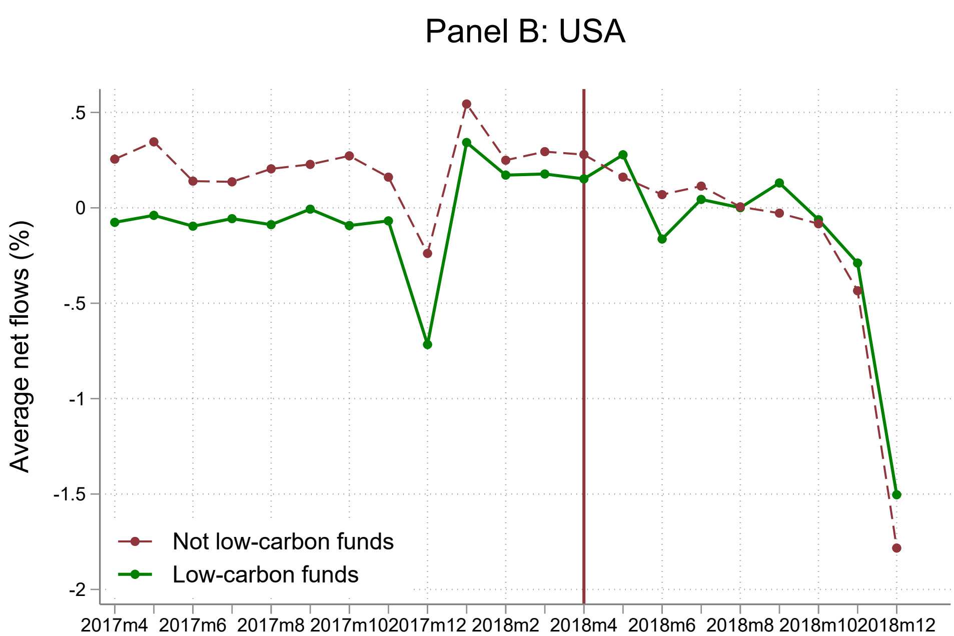
Consider first Panel A, showing the European sample. During the pre-publication period, the net flows in funds that would be later designated low-carbon are very similar to the average flows in other funds. Crucially for the validity of our difference-in-differences approach, the two groups show common trends. With the release of the LCD at the end of April 2018, low-carbon-designated funds started enjoying a clear and persistent increase of flows compared to other funds.

In the USA (Panel B), low-carbon funds show lower flows than conventional funds in the pre-publication period but, more importantly, again following very similar fluctuations.

Here, too, the release of the LCD in May 2018 seems to have triggered a relative boost of flows for LCD funds. In the following months there was some variation, though by the last four months of 2018, LCD funds had caught up to not-LCD funds in terms of monthly flows.

Figure 4: Effect of the LCD on fund flows
These figures show the equally-weighted average monthly flows of funds designated low-carbon at the end of April 2018 (solid green lines) and of conventional funds (dashed red line) domiciled in Europe (Panel A) and in the USA (Panel B), from April 2017 through December 2018. Flows are computed as of end of the month. The Low Carbon Designation was introduced at the end of April 2018.





5.2 Regression evidence

5.2.1 Empirical strategy

Figure 4 provides suggestive evidence that in the post-publication period, mutual funds that receive the Low Carbon Designation experience higher flows than mutual funds that do not receive it. To formally test that hypothesis, we run the following OLS regression explaining fund i's flows in month t from April 2017 through December 2018:

$$Flows_{i,t} = \alpha + \beta_1\ LCD_i\ \times\ Post_t + \beta_2\ LCD_i + \gamma' \mathbf{X_{i,t-1}} + \delta_{\mathbf{i,t}} + \eta_i +\ \epsilon_{i,t}. \qquad (1)$$

The main explanatory variable is the difference-in-differences interaction term $LCD_i \times Post_t$. LCD_i identifies funds that received the LCD at its initial release. $Post_t$ is an indicator variable equal to 1 for months after April 2018, and 0 for all prior months. $\mathbf{X_{i,t-1}}$ is a vector of time-varying lagged fund-level controls that, based on previous literature, may influence fund flows of LCD recipients in a differential manner. These are monthly returns in the previous three months, the logarithm of assets under management, return volatility, the fund's age, the fund's entrance or exit in the two extreme sustainability rating (Globes) categories, and changes of Morningstar's overall assessment of the fund (Stars).[24] $\delta_{\mathbf{i,t}}$ represents month-

[24]We use the change in sustainability and overall ratings rather than the absolute value because, as also noted in Hartzmark and Sussman (2019), if these rating systems are in equilibrium – e.g., existing investors have already sorted in low and high-sustainability funds according to their preferences, after an initial phase of reallocation – there is no reason to expect a continued flows-effect of ratings without further changes. That said, the results also hold just controlling for the number of Globes and the number of Stars.

by-style (Morningstar category) fixed effects. η_i is a set of country dummies (based on the fund's domicile). $\epsilon_{i,t}$ is the error term. Standard errors are clustered along both months and categories to account for cross-sectional dependence between observations.

5.2.2 Results

The regression results with our main specification are reported in columns (1), (3), and (6) of Table 5, using the full sample, European funds, and US funds, respectively. The coefficient on the DID interaction term is positive and highly statistically significant in each of the three samples. The coefficient in column (1) indicates that the assignment of the Low Carbon Designation is associated with an average 0.22 percentage points higher difference in net flows compared to the pre-publication period. This effect is economically important when compared to the effect of the main focus of the mutual funds literature so far, returns. A one standard deviation stronger performance in terms of monthly returns yields $3.33 \times 0.14 = 0.47$ percentage points more flows. In other words, the LCD is worth almost half ($0.22/0.47 = 47\%$) of a standard deviation in returns. When compounded over the eight months from May through December 2018, the flow premium associated with the LCD can be quantified in an increase of around 2% in the assets under management.

It is worth noticing that the statistically and economically important flows boost caused by the LCD happens independently of the effects of the general sustainability ratings documented in Ammann et al. (2018) and Hartzmark and Sussman (2019). Indeed, as shown in

Table A4, we find that the effect on flows of the LCD is stronger among low-sustainability than among high-sustainability funds, presumably because the former did not already have other means to target socially- and environmentally-conscious clients.[25]

The coefficients of the control variables are in line with previous literature. In particular, flows are negatively related to age and assets under management, and positively related to past financial performance (Patel et al., 1994).[26] Upgrades (downgrades) in terms of Morningstar's Stars are followed by a statistically significant increase (decrease) in flows.[27]

To limit the potential effects of size in determining monthly flows, we re-run the main DID analyses using normalized flows as dependent variable. The corresponding regression results are reported in models (2), (4) and (6) of Table 5. The effect of receiving the low-carbon label is again strongly statistically and economically significant: Net of the effects of control variables, on average, low-carbon funds move up 1.98 percentiles in net flows after April 2018, whereas a one standard deviation higher performance in the prior month results in a move up by 3.26 percentiles.

- Table 5 -

[25]This result is consistent with research suggesting that less visible funds (e.g., funds that engage is less marketing and funds without a five-star rating) have a higher flow sensitivity to salient features (Sirri and Tufano, 1998; Del Guercio and Tkac, 2008).

[26]Virtually unchanged results are obtained when using the returns adjusted for the average performance by category, and using CAPM-adjusted or Fama-French-adjusted returns. The results are also unaffected by controlling also for annual returns, or squared lagged quarterly or monthly returns to account for potential non-linear effects on flows.

[27]Thus, we expand the findings of Del Guercio and Tkac (2008) in our sample period. Ben-David et al. (2019) also show that Stars ratings are a major determinant of fund flows across US mutual funds, followed only by recent past returns. Huang et al. (2020) develop a model where investors take Stars ratings as reputation signals of funds' informational advantage.

We conduct a series of robustness checks to ensure the reliability of our findings. First, in Table A5 we confirm that our results hold – and indeed are larger in magnitude – when adding fund fixed effects to the regressions. Second, we interact all control variables with Post to allow for potential changes over time of the effects on flows of fund characteristics other than the LCD. As shown in Table A6 in the Appendix, the results continue to hold.

Third, in Table A7 we re-run the DID analysis weighting the observations by assets, ruling out the possibility that the coefficients on the LCD are driven by small funds. The same inferences hold.

Fourth, we add to the regression the two scores used to allocate the LCD – the Portfolio Carbon Risk (CR) and Fossil Fuel involvement (FFI) – and their interaction with Post. This test also provides potential insights into whether investors also responded, conditional on a fund receiving or not receiving the label, to the level of the underlying climate performance. No robust pattern emerges in Table A8 in the Appendix in this respect. Importantly, the results for our main coefficient of interest, the interaction of LCD with Post, remain virtually unchanged, confirming the role of the label in driving investor responses.

Finally, we repeat our analysis using a shorter pre-publication period, starting from December 2017. This allows us to exploit the availability of the LCDs for the period from December 2017 through April 2018, computed by applying the LCD methodology to the historical holdings. This setting allows to further rule out the possibility that the flow-effect of the LCD may be due to portfolio characteristics not explicitly related to climate performance. Results available on request show that our inferences hold when using the shorter pre-publication period (see Figure A2 in the Appendix for a graphical illustration).

Overall, our findings soundly reject the null hypothesis of no response to the introduction of the Low Carbon Designation. Investors in the mutual fund industry rewarded funds labeled as low-carbon with additional capital.

5.3 Effects of label upgrades and downgrades

We have shown that investors value climate responsibility, and rewarded funds labeled as low-carbon in April 2018. Was the release of the LCD a one-shot opportunity for funds to access the additional investment flows associated with being low-carbon?

Morningstar updates the LCD on a quarterly basis, with a one-month delay from the end of the quarter. Our sample period covers five quarterly updates in the post-publication period. As shown in Panel A of Table 6, while the large majority of funds had their LCD classification confirmed, in each of these updates a small fraction of funds did switch from LCD to not-LCD, or vice-versa. For each fund, we define the indicators *LCD Downgrade* and *LCD Upgrade*. These binary indicators are equal to 1 for months following an LCD downgrade or upgrade, respectively, and 0 otherwise.

The results in Panel B of Table 6 indicate that subsequent LCD upgrades and downgrades also have a significant impact on net flows. This is particularly the case for European funds. In the USA, where there are fewer "switchers" compared to the European sample, only the coefficient on LCD upgrades is statistically significant.

- Table 6 -

Overall, these result indicate that managers of funds that are not considered low-carbon can potentially access an important source of flows as long as they successfully manage to rebalance their portfolios in a low-carbon direction.

6 Mutual fund responses

The prior section has shown that investors in mutual funds have preferences for climate-conscious investments despite facing a higher idiosyncratic risk exposure. In this section we ask how strongly mutual fund managers react to these revealed preferences, and whether their allocation changes depend on their prior risk exposure. This is a novel contribution; while Ammann et al. (2018) and Hartzmark and Sussman (2019) document a flow effect due to Morningstar's Globes ratings, they do not study the supply-side reactions of fund managers.

6.1 Empirical strategy

To formally test how mutual funds changed their portfolios after the initial release of the LCD, we estimate difference-in-differences regressions. Our goal with this analysis is to shed light on the overall supply-side reaction of fund managers around an event that heightens awareness of climate-related risks and around which fund managers arguably noticed extra flows to low-carbon funds.[28] Here, it is intuitive to use as the treatment group those mutual funds that did *not* receive the LCD at its initial release. Specifically, we run the following regression explaining fund i's Carbon Risk in quarter q for quarters March 2017 through September 2019:

$$CR_{i,q} = \alpha + \beta_1 \ NotLCD_i \ \times \ Post_q + \beta_2 \ NotLCD_i + \gamma' \mathbf{X_{i,q-1}} + \delta_{\mathbf{i,q}} + \eta_i + \ \epsilon_{i,t}. \qquad (2)$$

The main explanatory variable is the difference-in-differences interaction term $NotLCD_i \times Post_q$. $NotLCD_i$ identifies funds that did not receive the LCD at its initial release. $Post_q$ is an indicator variable equal to 1 for the quarters the LCD was in place, i.e., 2018-Q2 through 2019-Q2, and 0 for all prior quarters. $\mathbf{X_{i,q-1}}$ includes quarterly time-varying lagged fund-level controls, analogue to specification (1) from the previous section. $\delta_{\mathbf{i,q}}$ includes quarter-by-style (Morningstar category) fixed effects. η_i is a set of country dummies (based on the fund's domicile). $\epsilon_{i,q}$ is the error term.

In this analysis, we exclude from our sample both explicit and closet indexers (around

[28]Our ambition thus is not to explicitly identify a causal effect of the LCD as such on fund manager behavior. If one were interested in the causal effect of the label itself, one might be inclined to consider a regression discontinuity (RD) design, because the LCD is awarded based on two thresholds. However, this method faces several challenges in our empirical setting: Importantly, treatment occurs every quarter, instead of being a one-shot event like entering a schooling program. In our setting, not only would we expect funds that barely did not receive the LCD to improve their climate performance, but also funds that barely got the LCD have an incentive to improve their climate performance since they risk losing the label in the next quarter. This can happen if low-carbon-risk firms underperform relative to high-carbon-risk firms, driving the portfolio CR score up. Additionally, the running variable (the fund's climate performance) is also our outcome variable, meaning that fund managers can "manipulate" their treatment status. This violates the validity requirements of the RD design (Lee and Lemieux, 2010).

12% of funds), which do not, by definition, follow active investment strategies.[29] We identify explicit indexers using the Morningstar definition, and closet indexers using the Active Share measures of Cremers and Petajisto (2009) and Cremers et al. (2016). In line with the previous studies, we use an active share below 60% as a cutoff for identifying a closet indexer. However, the portfolios of explicit and closet indexers still provide useful information, since we can use them as a benchmark for the changes we observe in the portfolio holdings of active funds.

Besides rebalancing activities, there are two additional ways through which the climate performance of mutual funds may change. First, these can originate from changes in the underlying carbon risk of firms. Second, they can originate from changes in market values of portfolio assets. We can exclude the first channel for most of our sample period since Sustainalytics updates the firms' climate scores on a yearly frequency, and all portfolio scores up to Q1-2019 are based on the firm-level carbon performance of 2017. Moreover, our results remain virtually unchanged if we drop the observations for Q2-2019 and Q3-2019, the only ones based on 2018 firm-level data. To account for the second channel, similarly to Leippold and Rueegg (2020), we benchmark the climate performance of active funds with that of funds that by definition, do *not* actively rebalance their portfolios, i.e., outright and closet indexers (together called passive funds). Our results remain unchanged if we use only the outright indexers as benchmark.

[29] As shown by Cremers and Petajisto (2009) and Cremers et al. (2016), a large number of so-called active funds are actually "closet indexers". Such funds are marketed as being actively managed, but their portfolios are mostly allocated passively according to an index.

Thus, for each quarter, *abnormal* CR is computed as the difference between the active fund's climate performance and the average climate performance of the passive funds in the same category. This way, we account for systematic differences between categories and across time. Additionally, to capture differences in levels, we perform the adjustment by the degree to which a fund fulfills the criteria for obtaining the LCD, i.e., ∅CR≤10, ∅FFI≤7%, both, or neither. We summarize this computation in equation 3 below.

$$AbnCR^{\tau}_{i,q,k} = CR^{\tau}_{i,q,k} - \varnothing CR^{Passive,\tau}_{q,k}, \ \forall \text{ fund } i, \text{ quarter } q, \text{ category } k, \text{ and} \quad \tau \in \{\varnothing\text{CR} \leq 10,\ \varnothing\text{FFI} \leq 7\%, \text{both, neither.}\} \tag{3}$$

Analogously to equations (2) and (3), we also run regressions explaining (abnormal) FFI.

6.2 Results

Table 7 shows our main results. Columns (1) and (3) use gross climate performance as the dependent variable and columns (2) and (4) use the abnormal climate performance, i.e., after controlling for the average CR and FFI of passive funds. All regressions include the full set of lagged fund-level controls, as well as quarter times style and country fixed effects. Standard errors are double clustered at the quarter and style level.

- Table 7 -

the coefficient on the DID interaction term is negative and highly statistically significant across specifications. For example, the interaction coefficient $NotLCD \times Post$ in column (1) indicates that funds that did not receive the LCD at its initial release on average decreased CR by 0.57 (17% of a standard deviation) more than funds that received the LCD in April 2018. When we account for differential changes in market capitalization of the underlying assets in column (2) we find that the size of the coefficient is similar, but the economic significance is somewhat stronger (26% of a standard deviation).

Columns (3) and (4) reveal a similar picture for Fossil Fuel Involvement (FFI). Overall, when compared to funds that received the LCD, not-LCD funds under-weighted their FFI by 0.49% (8% of a standard deviation) per quarter, or 3 percentage points when aggregated over the six quarters the LCD was in place. When we account for differential changes in market capitalization in column (4), we find that the actual improvement amounts to a 0.95% decrease in Abnormal FFI (22% of a standard deviation). The reason why adjusting for market trends is particularly important for FFI is that, in contrast to Carbon Risk, this variable is sector-specific and particularly prone to market swings.[30] We remove this bias when we control for the climate-performance of passive funds. We obtain similar results when we only control for the climate performance of outright indexers.

We conduct a series of checks to ensure the reliability of our findings. Panel A of Appendix Table A9 shows weighted regressions by a fund's assets under management. We do this to account for the possibility that the rebalancing we observe is simply a shift of high Carbon

[30]Consider an energy sector fund with a FFI of 70% and USD 100m in assets under management. Suppose that the fossil-fuel dependent stocks in its portfolio were to halve in value, whereas the value of the other stocks remains unchanged. If the fund were passive, its FFI would now be 0.5×70m /(0.5×70m + 30m), around 54%.

Risk firms from small funds to large funds. Our main findings are robust to this specification.

Panel B of Appendix Table A9 includes fund fixed effects. We do this to account for potential omitted variables that remain constant for a given fund. Despite the brief time series, the coefficients remain significant. These robustness tests mitigate omitted variables and selection bias concerns.

Overall, the evidence provided in this section is consistent with fund managers responding to the revealed preferences of their clients and the increased awareness of climate risks by improving the climate-performance of their portfolios.

7 Conclusion

Around the introduction of Morningstar's Low Carbon Designation (LCD) label in April 2018, mutual funds directly experienced the intensity of investors' preferences for climate-responsible investments: Funds labeled as low-carbon enjoyed a significant increase of assets under management from May through the end of December 2018 relative to funds that were not labeled as low-carbon. The quantities involved are substantial: Effectively, investors valued climate performance (receiving the LCD) as being equivalent to one half of a standard deviation of financial performance.

This result is noteworthy because the risk properties of LCD funds are quite different from those of funds with a high number of Morningstar ESG "Globes" (which investors are also fond of, as prior work by Hartzmark and Sussman (2019) has shown). In particular, funds with more globes have somewhat lower idiosyncratic risk but are likely to offer limited hedge against climate risk. By contrast, LCD funds offer such a hedge, but entail higher idiosyncratic risk relative to the market portfolio.

Changes in culinary habits and trends inspire chefs worldwide to adapt their menus to the new preferences of their clients. Similarly, with the chefs of the financial industry, investors' call for a low-carbon diet in their portfolios did not fall on deaf ears: Mutual funds that initially did not receive the LCD subsequently reduced (increased) their holdings in high (low) carbon-intensity companies. In other words, the release of climate-related information is likely to have accelerated the adoption of climate-related investment strategies in the mutual fund industry.

The high-carbon assets shunned by mutual funds seeking to be considered low-carbon do not disappear, but are picked up by other investors. However, this type of divestment is likely to increase the cost of capital for high-carbon firms, much like the divestment from "sin stocks" by certain norm-constrained investors increases the cost of capital (and the expected returns) of companies involved in alcohol, tobacco, or gambling-related activities (Hong and Kacperczyk, 2009). Whether and how this will induce high-carbon firms to attempt to convert their business models toward cleaner business activities remains unclear.[31]

A full analysis of these dynamics, including welfare considerations, is outside the scope of

[31] For instance, in Oehmke and Opp (2020) socially responsible investors can indeed lead firms to adopt clean production technologies, but only under certain conditions. In particular, in their model, socially responsible investors need to have a broad mandate – i.e., the ability to also invest in "dirty" firms – in order to generate impact.

this paper. Even with this caveat, we believe that the results have important implications for fund managers, policy-makers, and investors. First, they alert active fund managers to the importance of sustainability as a key competitive edge, especially in light of the return and fee pressure coming from index funds and ETFs. Second, our analyses can inform policy-makers and investors of the potential effectiveness of eco-labeling schemes in re-orienting capital flows. On the one hand, they "work" in the sense of inducing desired behavioral responses by market participants. On the other hand, certain designs of eco-labels may incentivize funds to reduce diversification, to the potential detriment of investors. Policy-makers trying to partially outsource the decarbonisation of the economy to financial markets should be aware of such potential undesired effects.

References

Alok, Shashwat, Nitin Kumar, and Russ Wermers, 2020, Do fund managers misestimate climatic disaster risk?, *Review of Financial Studies* 33, 1146–1183.

Ammann, Manuel, Christopher Bauer, Sebastian Fischer, and Philipp Muller, 2018, The impact of the Morningstar sustainability rating on mutual fund flows, *European Financial Management* 1, 1–34.

Anderson, Anders, and David T. Robinson, 2019, Knowledge, fear and beliefs: Understanding household demand for green investments, Working Paper.

Andersson, Mats, Patrick Bolton, and Frédéric Samama, 2016, Hedging climate risk, *Financial Analysts Journal* 72, 13–32.

Ang, Andrew, Robert J. Hodrick, Yuhang Xing, and Xiaoyan Zhang, 2006, The cross-section of volatility and expected returns, *The Journal of Finance* 61, 259–299.

Ang, Andrew, Robert J. Hodrick, Yuhang Xing, and Xiaoyan Zhang, 2009, High idiosyncratic volatility and low returns: International and further US evidence, *Journal of Financial Economics* 91, 1–23.

Bali, Turan G., Nusret Cakici, Xuemin Yan, and Zhe Zhang, 2005, Does idiosyncratic risk really matter?, *The Journal of Finance* 60, 905–929.

Barber, Brad M., Adair Morse, and Ayako Yasuda, 2020, Impact investing, *Journal of Financial Economics* Forthcoming.

Bassen, Alexander, Katrin Gödker, Florian Lüdeke-Freund, and Josua Oll, 2018, Climate information in retail investors' decision-making: Evidence from a choice experiment, *Organization & Environment* 1–21.

Bauer, Rob, Tobias Ruof, and Paul Smeets, 2018, Get real! Individuals prefer more sustainable investments, Working Paper.

Ben-David, Itzhak, Jiacui Li, Andrea Rossi, and Yang Song, 2019, What do mutual fund investors really care about?, Working Paper.

Berk, Jonathan B., and Richard C. Green, 2004, Mutual fund flows and performance in rational markets, *Journal of Political Economy* 112, 1269–1295.

Berk, Jonathan B., and Jules H. Van Binsbergen, 2015, Measuring skill in the mutual fund industry, *Journal of Financial Economics* 118, 1–20.

Bialkowski, Jedrzej, and Laura T. Starks, 2016, SRI funds: Investor demand, exogenous shocks and ESG profiles, Working Paper.

Bollen, Nicolas P.B., 2007, Mutual fund attributes and investor behavior, *Journal of Financial and Quantitative Analysis* 42, 683–708.

Bolton, Patrick, and Marcin T. Kacperczyk, 2020, Do investors care about carbon risk?, *Journal of Financial Economics* Forthcoming.

Bolton, Patrick, and Marcin T. Kacperczyk, 2021, Global pricing of carbon-transition risk, Working paper.

Bonnefon, Jean-Francois, Augustin Landier, Parinitha Sastry, and David Thesmar, 2019, Do investors care about corporate externalities? Experimental evidence, Working Paper.

Chen, Huaizhi, Lauren Cohen, and Umit Gurun, 2021, Don't take their word for it: The misclassification of bond mutual funds, *The Journal of Finance* Forthcoming.

Chevalier, Judith, and Glenn Ellison, 1997, Risk taking by mutual funds as a response to incentives, *Journal of Political Economy* 105, 1167–1200.

Choi, Darwin, Zhenyu Gao, and Wenxi Jiang, 2021, Global carbon divestment and firms' actions, Working Paper.

Clifford, Christopher P., Jon A. Fulkerson, Russell Jame, and Bradford D Jordan, 2020, Salience and mutual fund investor demand for idiosyncratic volatility, *Management Science* Forthcoming.

Coase, Ronald, 1960, The problem of social cost, *Journal of Law, Economics, and Organization* 3, 1–44.

Cooper, Michael J., Huseyin Gulen, and P. Raghavendra Rau, 2005, Changing names with style: Mutual fund name changes and their effects on fund flows, *The Journal of Finance* 60, 2825–2858.

Cremers, K. J. Martijn, and Antti Petajisto, 2009, How active is your fund manager? A new measure that predicts performance, *Review of Financial Studies* 22, 3329–3365.

Cremers, Martijn, Miguel A. Ferreira, Pedro Matos, and Laura Starks, 2016, Indexing and active fund management: International evidence, *Journal of Financial Economics* 120, 539–560.

Del Guercio, Diane, and Paula A. Tkac, 2008, Star power: The effect of Morningstar ratings on mutual fund flow, *Journal of Financial and Quantitative Analysis* 43, 907–936.

Donaldson, Jason Roderick, and Giorgia Piacentino, 2018, Contracting to compete for flows, *Journal of Economic Theory* 173, 289–319.

Döttling, Robin, and Sehoon Kim, 2020, Sustainability preferences under stress: Evidence from mutual fund flows during COVID-19, Working Paper.

Dyck, Alexander, Karl V. Lins, Lukas Roth, and Hannes F. Wagner, 2019, Do institutional investors drive corporate social responsibility? International evidence, *Journal of Financial Economics* 131, 693–714.

Elton, Edwin J., 1999, Presidential address: Expected return, realized return, and asset pricing tests, *The Journal of Finance* 54, 1199–1220.

Engle, Robert F, Stefano Giglio, Bryan Kelly, Heebum Lee, and Johannes Stroebel, 2020, Hedging climate change news, *Review of Financial Studies* 33, 1184–1216.

European Commission, 2018, Action plan for sustainable finance, Available at `https://ec.europa.eu/info/publications/180308-action-plan-sustainable-growth_en`.

European Parliament and Council, 2020, Regulation on sustainability-related disclosures in the financial services sector, Available at `https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX:32019R2088`.

Evans, Richard B, and Yang Sun, 2021, Models or stars: The role of asset pricing models and heuristics in investor risk adjustment, *Review of Financial Studies* 34, 67–107.

Fernando, Chitru S., Mark P. Sharfman, and Vahap B. Uysal, 2017, Corporate environmental policy and shareholder value: Following the smart money, *Journal of Financial and Quantitative Analysis* 52, 2023–2051.

Flammer, Caroline, 2021, Corporate green bonds, *Journal of Financial Economics* Forthcoming.

Gabaix, Xavier, 2012, Variable rare disasters: An exactly solved framework for ten puzzles in macro-finance, *The Quarterly Journal of Economics* 127, 645–700.

Geczy, Christopher, Robert F. Stambaugh, and David Levin, 2021, Investing in socially responsible mutual funds, *Review of Asset Pricing Studies* Forthcoming.

Gibson, Rajna, Simon Glossner, Philipp Krüger, Pedro Matos, and Tom Steffen, 2019, Responsible institutional investing around the world, Working Paper.

Gibson, Rajna, and Philipp Krüger, 2020, The sustainability footprint of institutional investors, Working Paper.

Godfrey, Paul C., Craig B. Merrill, and Jared M. Hansen, 2009, The relationship between corporate social responsibility and shareholder value: An empirical test of the risk management hypothesis, *Strategic Management Journal* 30, 425–445.

Goetzmann, William N., and Alok Kumar, 2008, Equity portfolio diversification, *Review of Finance* 12, 433–463.

Goyal, Amit, and Pedro Santa-Clara, 2003, Idiosyncratic risk matters!, *The Journal of Finance* 58, 975–1007.

Guercio, Diane Del, and Jonathan Reuter, 2014, Mutual fund performance and the incentive to generate alpha, *The Journal of Finance* 69, 1673–1704.

Harris, Lawrence E., Samuel M. Hartzmark, and David H. Solomon, 2015, Juicing the dividend yield: Mutual funds and the demand for dividends, *Journal of Financial Economics* 116, 433–451.

Hartzmark, Samuel M., and Abigail B. Sussman, 2019, Do investors value sustainability? A natural experiment examining ranking and fund flows, *The Journal of Finance,* 74, 2789–2837.

Heinkel, Robert, Alan Kraus, and Josef Zechner, 2001, The effect of green investment on corporate behavior, *Journal of Financial and Quantitative Analysis* 36, 431–449.

Hong, Harrison, and Marcin Kacperczyk, 2009, The price of sin: The effects of social norms on markets, *Journal of Financial Economics* 93, 15–36.

Hong, Harrison, and Leonard Kostovetsky, 2012, Red and blue investing: Values and finance, *Journal of Financial Economics* 103, 1–19.

Hortaçsu, Ali, and Chad Syverson, 2004, Product differentiation, search costs, and competition in the mutual fund industry: A case study of S&P 500 index funds, *The Quarterly Journal of Economics* 119, 403–456.

Huang, Chong, Fei Li, and Xi Weng, 2020, Star ratings and the incentives of mutual funds, *The Journal of Finance,* 75, 1715–1765.

Huang, Wei, Qianqiu Liu, S. Ghon Rhee, and Liang Zhang, 2010, Return reversals, idiosyncratic risk, and expected returns, *Review of Financial Studies* 23, 147–168.

Huberman, Gur, and Wei Jiang, 2006, Offering versus choice in 401 (k) plans: Equity exposure and number of funds, *The Journal of Finance* 61, 763–801.

Huynh, Thanh, and Ying Xia, 2020, Climate change news risk and corporate bond returns, *Journal of Financial and Quantitative Analysis* Forthcoming.

Ilhan, Emirhan, Philipp Krueger, Zacharias Sautner, and Laura T. Starks, 2020, Climate risk disclosure and institutional investors.

Ilhan, Emirhan, Zacharias Sautner, and Grigory Vilkov, 2021, Carbon tail risk, *Review of Financial Studies* 3, 1540–1571.

Investment Company Institute, ICI, 2019, Investment company fact book, Available at `www.ici.org`.

Kacperczyk, Marcin, Stijn Van Nieuwerburgh, and Laura Veldkamp, 2014, Time-varying fund manager skill, *The Journal of Finance* 69, 1455–1484.

Kacperczyk, Marcin, Clemens Sialm, and Lu Zheng, 2005, On the industry concentration of actively managed equity mutual funds, *The Journal of Finance* 60, 1983–2011.

Kempf, Alexander, and Stefan Ruenzi, 2008, Tournaments in mutual-fund families, *The Review of Financial Studies* 21, 1013–1036.

Krüger, Philipp, 2015, Corporate goodness and shareholder wealth, *Journal of Financial Economics* 115, 304–329.

Krüger, Philipp, Zacharias Sautner, and Laura T. Starks, 2020, The importance of climate risks for institutional investors, *Review of Financial Studies* 33, 1067–1111.

Lee, David S., and Thomas Lemieux, 2010, Regression discontinuity designs in economics, *Journal of Economic Literature* 48, 281–355.

Leippold, Markus, and Roger Rueegg, 2020, How rational and competitive is the market for mutual funds?, *Review of Finance* 24, 579–613.

Lins, Karl V., Henri Servaes, and Ane Tamayo, 2017, Social capital, trust, and firm performance: The value of corporate social responsibility during the financial crisis, *The Journal of Finance* 72, 1785–1824.

Markowitz, Harry, 1952, Portfolio selection, *The Journal of Finance* 7, 77–91.

Maxfield, Sylvia, and Liu Wang, 2020, Does sustainable investing reduce portfolio risk? A multilevel analysis, *European Financial Management* .

Morningstar, 2018a, Measuring transition risk in fund portfolios, available at: `https://www.morningstar.com/lp/measuring-transition-risk`.

Morningstar, 2018b, Morningstar Low Carbon Designation, available at: `https://s21.q4cdn.com/198919461/files/doc_news/2018/Morningstar-Low-Carbon-Designation-Methodology-Final.pdf`.

Nordhaus, William, 2019, Climate change: The ultimate challenge for economics, *American Economic Review* 109, 1991–2014.

Oehmke, Martin, and Marcus M. Opp, 2020, A theory of socially responsible investment, Working Paper.

Pástor, Ľuboš, Robert F. Stambaugh, and Lucian A. Taylor, 2020a, Fund tradeoffs, *Journal of Financial Economics* 138, 614–634.

Pástor, Ľuboš, and M. Blair Vorsatz, 2020, Mutual fund performance and flows during the COVID-19 crisis, *The Review of Asset Pricing Studies* 10, 791–833.

Pástor, Ľuboš, Robert F. Stambaugh, and Lucian A. Taylor, 2017, Do funds make more when they trade more?, *The Journal of Finance* 72, 1483–1528.

Pástor, Ľuboš, Robert F. Stambaugh, and Lucian A. Taylor, 2020b, Sustainable investing in equilibrium, *Journal of Financial Economics* Forthcoming.

Patel, Jayendu, Richard J. Zeckhauser, and Darryll Hendricks, 1994, Investment flows and performance: Evidence from mutual funds, cross-border investments, and new issues, in Ryuzo Sato, Richard Levich, and Rama Ramachandran, eds., *Japan, Europe and the International Financial Markets: Analytical and Empirical Perspectives*, 51–72 (New York, NY: Cambridge University Press).

Pedersen, Lasse Heje, Shaun Fitzgibbons, and Lukasz Pomorski, 2020, Responsible investing: The ESG-efficient frontier, *Journal of Financial Economics* Forthcoming.

Pigou, Arthur C., 1920, *The Economics of Welfare* (MacMillan, London).

Ramelli, Stefano, Alexander F. Wagner, Richard J. Zeckhauser, and Alexandre Ziegler, 2021, Investor rewards to climate responsibility: Stock-price responses to the opposite shocks of the 2016 and 2020 U.S. elections, *Review of Corporate Financial Studies* Forthcoming.

Renneboog, Luc, Jenke Ter Horst, and Chendi Zhang, 2008, The price of ethics and stakeholder governance: The performance of socially responsible mutual funds, *Journal of Corporate Finance* 14, 302–322.

Renneboog, Luc, Jenke Ter Horst, and Chendi Zhang, 2011, Is ethical money financially smart? Nonfinancial attributes and money flows of socially responsible investment funds, *Journal of Financial Intermediation* 20, 562–588.

Riedl, Arno, and Paul Smeets, 2017, Why do investors hold socially responsible mutual funds?, *The Journal of Finance* 72, 2505–2550.

Sirri, Erik R., and Peter Tufano, 1998, Costly search and mutual fund flows, *The Journal of Finance* 53, 1589–1622.

Tsai, Jerry, and Jessica A Wachter, 2015, Disaster risk and its implications for asset pricing, *Annual Review of Financial Economics* 7, 219–252.

Wachter, Jessica A., 2013, Can time-varying risk of rare disasters explain aggregate stock market volatility?, *The Journal of Finance* 68, 987–1035.

Wahal, Sunil, and Albert Yan Wang, 2011, Competition among mutual funds, *Journal of Financial Economics* 99, 40–59.

Weitzman, Martin, 1974, Prices versus quantities, *Review of Economic Studies* XLI, 477–491.

Weitzman, Martin L., 2009, On modeling and interpreting the economics of catastrophic climate change, *The Review of Economics and Statistics* 91, 1–19.

Weitzman, Martin L, 2011, Fat-tailed uncertainty in the economics of catastrophic climate change, *Review of Environmental Economics and Policy* 5, 275–292.

Tables

Table 1: Descriptive statistics

Descriptive statistics of active mutual funds domiciled in Europe and USA for which information on the Low Carbon Designation (LCD) and flows is available. Panel A covers all fund-month observations from April 2017 through September 2019, while Panel B provides a snapshot as of the end of April 2018. LCD is a dummy variable indicating funds that obtained the Low Carbon Designation at the end of April 2018. CR and FFI are the funds' carbon risk and fossil fuel involvement. Abn CR and Abn FFI are the funds' climate performance after controlling for differential market performance. Flows (in percentage points) is the monthly growth of assets net of reinvested returns. Normalized flows are computed following Hartzmark and Sussman (2019). Return is the monthly net return. Log assets is the log of AUM in USD. Volatility is the standard deviation of returns in the previous 12 months. Expense ratio is the annual percentage of assets deducted for fund expenses. Age is the number of years since the inception of the oldest share class. Globes is the Morningstar sustainability rating on a 1-5 scale. Stars is the overall Morningstar rating system on a 1-5 scale. Δ1 Globe and Δ5 Globes indicate funds entering (1) or exiting (-1) the 1 Globe and 5 Globes category in a given month. ΔStars indicates if a fund received a downgrade or an upgrade in the Morningstar rating system (Stars). Socially conscious is a dummy variable for funds that label themselves as socially conscious in either their name or prospectus. Institutional is a dummy variable for funds with more than 90% of assets in institutional share classes. Idiosyncratic risk is the standard deviation of residuals from a Fama-French three-factor model run over the period from December 2016 through April 2018, funds with at least 12 observations of monthly returns.

Panel A: From April 2017 through September 2019

	N	min	p25	mean	p50	p75	max	sd
LCD	392,417	0.00	0.00	0.18	0.00	0.00	1.00	0.38
CR	244,879	0.23	8.37	10.13	10.05	11.44	45.60	3.42
FFI	346486	0.00	3.03	6.98	6.17	9.50	92.73	5.83
Flows	392,417	-19.54	-1.53	0.07	-0.23	1.29	30.66	3.99
Normalized flows	392,417	1.00	27.00	50.27	50.00	73.00	100.00	27.20
Return	392,417	-99.71	-1.08	0.41	0.61	2.23	26.21	3.33
Log assets	392,417	4.69	16.76	18.34	18.30	19.82	26.02	2.10
Volatility	392,417	0.01	1.73	2.78	2.51	3.57	28.72	1.48
Expense ratio	189,481	-0.25	0.73	1.13	1.07	1.46	15.15	0.69
Age	392,417	0.16	5.49	13.47	12.08	18.66	119.32	10.26
Globes	284,513	1.00	2.00	3.05	3.00	4.00	5.00	1.13
Stars	235,777	1.00	2.00	3.15	3.00	4.00	5.00	1.06
Δ1 Globe	392,417	-1.00	0.00	-0.00	0.00	0.00	1.00	0.13
Δ5 Globes	392,417	-1.00	0.00	0.00	0.00	0.00	1.00	0.13
ΔStars	392,417	-1.00	0.00	-0.00	0.00	0.00	1.00	0.30
Socially conscious	392,417	0.00	0.00	0.10	0.00	0.00	1.00	0.30
Institutional	392,417	0.00	0.00	0.19	0.00	0.00	1.00	0.40
Idiosyncratic risk	299,075	0.00	0.87	1.51	1.48	2.00	17.06	0.82

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Panel B: End of April 2018

	N	min	p25	mean	p50	p75	max	sd
LCD	13,465	0.00	0.00	0.18	0.00	0.00	1.00	0.38
CR	9,251	0.23	9.02	10.68	10.61	11.92	45.58	3.44
FFI	13,419	0.00	2.92	6.66	5.89	9.05	70.99	5.50
Flows	13,465	-19.27	-2.20	-0.89	-1.55	-0.00	30.48	3.87
Normalized flows	13,465	1.00	27.00	49.68	49.00	73.00	100.00	27.33
Return	13,465	-9.79	0.47	2.04	1.81	3.45	13.91	2.10
Log assets	13,465	7.14	16.79	18.36	18.32	19.85	25.93	2.09
Volatility	13,465	0.07	1.73	2.25	2.30	2.73	9.20	0.81
Expense ratio	6,338	-0.21	0.72	1.14	1.07	1.45	14.53	0.72
Age	13,465	0.16	5.07	13.11	11.71	18.33	118.24	10.28
Globes	9,595	1.00	2.00	3.02	3.00	4.00	5.00	1.14
Stars	9,842	1.00	2.00	3.16	3.00	4.00	5.00	1.05
Δ1 Globe	13,465	-1.00	0.00	-0.00	0.00	0.00	1.00	0.15
Δ5 Globes	13,465	-1.00	0.00	0.00	0.00	0.00	1.00	0.14
ΔStars	13,465	-1.00	0.00	0.01	0.00	0.00	1.00	0.32
Socially conscious	13,465	0.00	0.00	0.10	0.00	0.00	1.00	0.30
Institutional	13,465	0.00	0.00	0.20	0.00	0.00	1.00	0.40
Idiosyncratic risk	13,028	0.09	0.94	1.57	1.46	2.11	10.92	0.85

Table 2: Geographical distribution of funds
This table shows the geographical distribution of funds included in the sample, with the share of funds that obtained the Morningstar Low Carbon Designation. Standard deviations and 25th, 50th, and 75th percentiles of flows for each area are reported to facilitate the interpretation of regression results that follow. The table covers all funds included in the sample as of April 2018. Portfolio Carbon Risk Scores are assigned by Morningstar only to funds with more than 67% of portfolio assets in companies covered by Sustainalytics in terms of carbon-risk rating (Morningstar, 2018b).

			Flows			
Area of domicile	N	Fraction of LCD funds	p25	p50	p75	sd
Europe	9,266	0.18	-2.58	-1.80	-0.87	3.90
USA	4,199	0.17	-1.00	-0.23	0.75	3.51
Total	13,465	0.18	-2.20	-1.55	-0.00	3.87

Table 3: Morningstar LCD, sustainability, and overall ratings
This table shows the absolute frequencies of funds without and with the Low Carbon Designation (LCD) along the Morningstar sustainability "Globes" ratings (Panel A) and the Morningstar overall "Stars" ratings (Panel B) as of April 2018.

Panel A: Morningstar sustainability ratings ("Globes")

LCD	1	2	3	4	5	Total
0	858	1,671	2,595	1,619	703	7,446
1	183	366	677	581	342	2,149
Total	1,041	2,037	3,272	2,200	1,045	9,595
% of LCD funds	17.58%	17.97%	26.09%	26.41%	32.72.41%	22.40%

Panel B: Morningstar overall ratings ("Stars")

LCD	1	2	3	4	5	Total
0	497	1,618	2,898	2,062	736	7,811
1	86	368	682	604	291	2,031
Total	583	1,986	3,580	2,666	1,027	9,842
% of LCD funds	14.75%	18.53%	19.05%	22.66%	28.33%	20.64%

Table 4: Low-carbon funds have higher idiosyncratic volatility
This table shows regressions of funds' idiosyncratic risk on decile indicators along funds' carbon risk (CR) (column (1)), fossil fuel involvement (FFI) (column (2)), and ESG sustainability score (column 3). *Idiosyncratic volatility* is computed as the standard deviation of residuals from Fama-French three-factor model regressions over the period from December 2017 through April 2018, when at least 12 observations of monthly returns are available. *FF3 alpha* is the estimated intercept from these regressions. t-statistics based on robust standard errors are reported in parentheses. ***, **, and * indicate that the parameter estimate is significantly different from zero at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)
Dependent variable:	Idiosyncratic volatility		
Sorting variable:	CR	FFI	ESG score
Decile = 1	0.06***	0.21***	0.52***
	(2.61)	(8.48)	(9.90)
Decile = 2	0.05**	0.05**	0.24***
	(2.23)	(2.33)	(7.41)
Decile = 3	0.04*	0.01	0.08***
	(1.78)	(0.65)	(2.83)
Decile = 4	0.01	0.00	0.07***
	(0.53)	(0.11)	(2.58)
Decile = 6	0.00	0.02	-0.04*
	(0.19)	(1.08)	(-1.79)
Decile = 7	0.02	0.06***	-0.05*
	(0.83)	(3.41)	(-1.86)
Decile = 8	0.04**	0.07***	-0.11***
	(2.06)	(3.72)	(-3.87)
Decile = 9	0.10***	0.13***	-0.17***
	(4.82)	(6.90)	(-5.80)
Decile = 10	0.31***	0.25***	-0.14***
	(10.81)	(9.91)	(-4.97)
Log assets	-0.02***	-0.03***	-0.03***
	(-5.67)	(-9.41)	(-8.36)
FF3 alpha	0.13***	0.14***	0.11***
	(5.33)	(5.60)	(4.05)
Constant	1.88***	1.91***	2.17***
	(34.58)	(35.50)	(29.52)
Observations	8,968	12,981	9,447
R-squared	0.58	0.56	0.52
Category FE	Yes	Yes	Yes
Country FE	Yes	Yes	Yes

Table 5: Investors prefer low-carbon funds

This table shows results of OLS difference-in-differences (DID) regressions of monthly flows from April 2017 through December 2018 on Low Carbon Designation (LCD), the interaction of this variable with a dummy Post equal to 1 for months following April 2018 (publication period). The sample includes active equity and diversified mutual funds domiciled in Europe or USA, excluding funds that experienced an LCD upgrade or downgrade in August or November 2018. Models (1), (3) and (5) use monthly net flows as the dependent variable, while models (2), (4), and (6) use monthly normalized flows. All regressions control for lagged fund characteristics, and month-by-style and country fixed effects. The direct effect of the dummy Post is absorbed by the time fixed effects. Singleton observations are dropped. t-statistics, based on robust standard errors clustered at the style and month level, are reported in parentheses. ***, **, and * indicate that the parameter estimate is significantly different from zero at the 1%, 5%, and 10% level, respectively.

	Full sample		Europe		USA	
Dep. variable:	(1) Flows	(2) Normalized flows	(3) Flows	(4) Normalized flows	(5) Flows	(6) Normalized flows
LCD × Post	0.22***	1.98**	0.26***	2.34**	0.23**	1.91***
	(3.16)	(2.53)	(3.60)	(2.49)	(2.53)	(3.49)
LCD	0.11	0.78	0.08	0.66	0.09	0.28
	(0.99)	(0.95)	(0.64)	(0.74)	(0.80)	(0.30)
Return	0.14***	0.98**	0.15***	1.00***	0.21***	1.57***
	(3.85)	(2.64)	(5.08)	(3.50)	(11.32)	(8.14)
Return t-2	0.12***	0.95***	0.11***	0.85***	0.21***	1.77***
	(4.36)	(3.30)	(5.01)	(3.56)	(7.24)	(6.08)
Return t-3	0.15***	1.25***	0.12***	0.95***	0.25***	2.07***
	(3.66)	(3.14)	(3.22)	(2.89)	(6.82)	(7.27)
Log assets	-0.04*	0.60*	-0.01	0.94**	-0.07***	0.29
	(-1.92)	(1.80)	(-0.62)	(2.59)	(-3.52)	(0.79)
Volatility	0.05	0.50	0.02	0.02	0.01	0.69
	(0.69)	(0.82)	(0.39)	(0.06)	(0.08)	(0.46)
Age	-0.04***	-0.40*	-0.05***	-0.38***	-0.04***	-0.42***
	(-6.19)	(-1.79)	(-6.76)	(-7.08)	(-3.84)	(-4.73)
Δ1 Globe	-0.04	0.36	0.01	0.62	-0.08	0.38
	(-0.65)	(1.48)	(0.16)	(1.49)	(-1.01)	(1.23)
Δ5 Globes	0.10	0.28	0.09	0.17	0.09	-0.03
	(1.21)	(0.43)	(1.01)	(0.28)	(1.10)	(-0.10)
ΔStars	0.06*	0.23	0.09*	0.39	0.01	-0.13
	(2.07)	(0.90)	(2.03)	(1.04)	(0.37)	(-0.67)
Observations	261,361	261,361	178,267	178,267	83,087	83,087
R-squared	0.17	0.13	0.22	0.13	0.09	0.24
Month-style FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Month-style clustered SE	Yes	Yes	Yes	Yes	Yes	Yes

Table 6: Effects of LCD downgrades and upgrades through September 2019
Panel A of this table summarizes the results of the quarterly LCD updates that took place between May 2018 and September 2019 at a quarterly frequency, based on the portfolio holdings as at the end of each quarter. Panel B shows results of OLS regressions of monthly flows from May 2018 through September 2019 on *LCD Downgrade* and *LCD Upgrade*, and control variables (monthly, returns in the previous three months, volatility, log asset, age, Δ1 Globe, Δ5 Globes, ΔStars). *LCD Downgrade* and *LCD Upgrade* are dummy variables equal to 1 for months following an LCD downgrade or upgrade, and 0 otherwise. All regressions control for month-by-style and country fixed effects. t-statistics, based on robust standard errors clustered at the style and month level, are reported in parentheses. ***, **, and * indicate that the parameter estimate is significantly different from zero at the 1%, 5%, and 10% level, respectively.

Panel A: LCD changes after April 2018

LCD updates	Aug 2018 (Q2-2018)	Nov 2018 (Q3-2018)	Feb 2019 (Q4-2018)	May 2019 (Q1-2019)	Aug 2019 (Q2-2019)
Downgrades	206	324	412	555	593
Confirmations	13,045	12,625	12,280	12,388	12,215
Upgrades	140	302	474	582	733

Panel B: Effect of LCD changes after April 2018

	Full sample		Europe		USA	
Dep. variable:	(1) Flows	(2) Normalized flows	(3) Flows	(4) Normalized flows	(5) Flows	(6) Normalized flows
LCD Downgrade	-0.18**	-0.80	-0.20**	-0.88*	-0.04	0.04
	(-2.57)	(-1.46)	(-2.63)	(-1.92)	(-0.27)	(0.02)
LCD Upgrade	0.21**	1.41**	0.21**	1.30***	0.19	1.56
	(2.62)	(2.21)	(2.91)	(2.95)	(0.70)	(0.69)
Observations	228,446	228,446	158,703	158,703	69,736	69,736
R-squared	0.10	0.12	0.13	0.12	0.07	0.19
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Month-style FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Month-style clustered SE	Yes	Yes	Yes	Yes	Yes	Yes

Table 7: Funds tilt portfolios towards low-carbon firms

This table shows results of OLS regressions of quarterly gross and Abnormal Carbon Risk (CR and Abn CR) and Fossil Fuel Involvement (FFI and Abn FFI) from March 2017 through September 2019 on a dummy, Post, indicating the period after April 2018. Abnormal climate performance metrics (indicated by Abn) are constructed to account for price changes by subtracting for each category-month pair the mean CR and FFI of explicit indexers and passive investors (Active Share ≤60%). The sample includes active funds domiciled in Europe or the US. We compute the means separately by the degree to which the treatment criteria are fulfilled, i.e., ∅CR≤10, ∅FFI≤7, both, and none. All regressions control for quarter-by-style fixed effects and lagged fund-level controls. Singleton observations are dropped. t-statistics, based on robust standard errors clustered at the quarter and category are reported in parentheses. ***, **, and * indicate that the parameter estimate is significantly different from zero at the 1%, 5%, and 10% level, respectively.

Dep. variable:	(1) CR	(2) Abn CR	(3) FFI	(4) Abn FFI
NotLCD × Post	-0.61***	-0.34***	-0.49***	-0.95***
	(-5.83)	(-3.53)	(-4.02)	(-4.19)
NotLCD	3.56***	0.40*	6.12***	0.37
	(27.37)	(2.24)	(16.78)	(0.86)
Observations	59,252	59,252	59,252	59,252
R-squared	0.62	0.12	0.44	0.09
Controls	Yes	Yes	Yes	Yes
Quarter-style FE	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Quarter-style clustered FE	Yes	Yes	Yes	Yes

Supplementary (Online) Appendix

Figure A1: Sustainability Globes, loading on negative climate new, and idiosyncratic risk

These figures show binned scatter plots of funds' climate news beta (Panel A) and idiosyncratic risk (Panel B) against funds' Morningstar Globes ratings, controlling for category fixed effects and log assets.

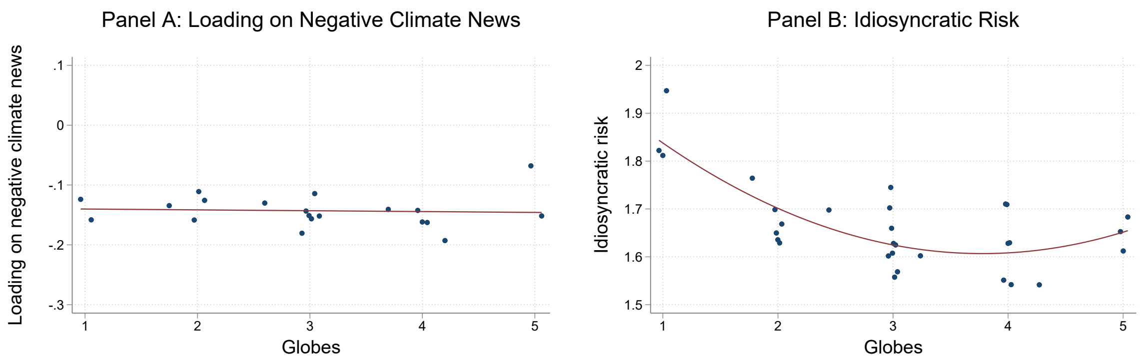
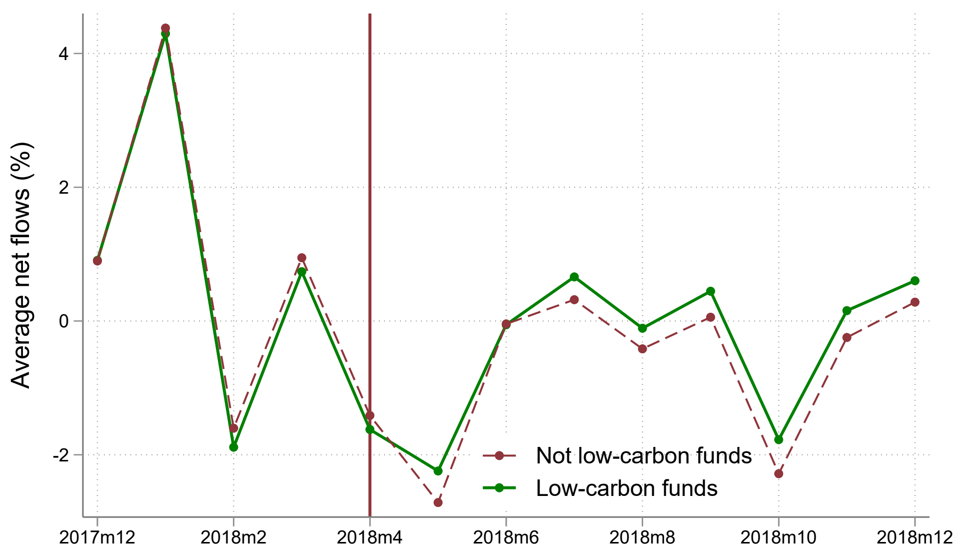


Figure A2: Investors prefer low-carbon funds - Robustness check: Shorter pre-publication period with pre-publication labels

These figures show the equally-weighted average monthly flows from December 2017 through December 2018 of European (top) and US (bottom) funds that had portfolios with low-carbon features (solid green lines) and of those that did not (dashed red line). These graphs leverage on the availability of LCD data from December 2017 to April 2018 (pre-publication period). Flows are computed as of end of the month.

Panel A: Europe



Panel B: USA

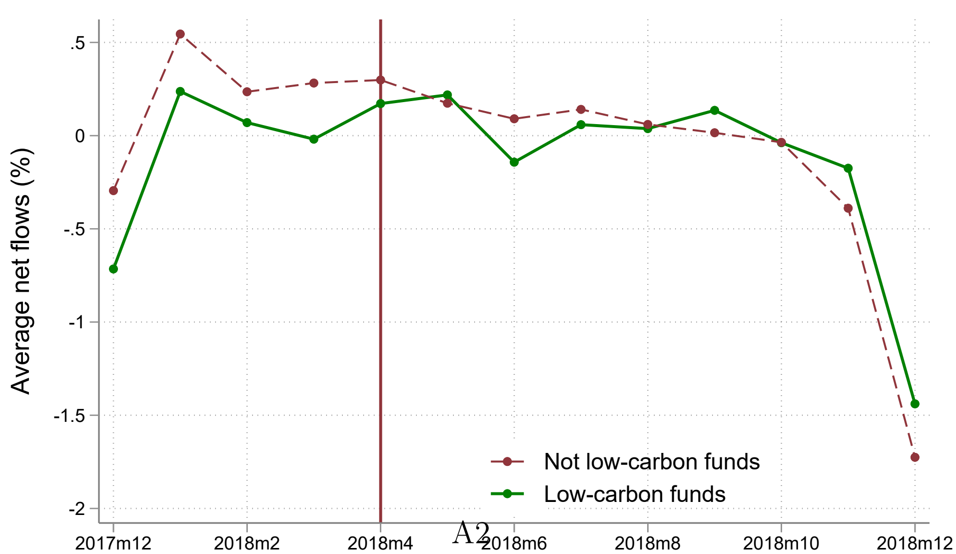


Table A1: : Firm-level Carbon Risk scores by GICS sectors
This table shows the descriptive statistics of 2017 firm-level Carbon Risk scores from the ESG research provider Sustainalytics, by GICS sector. Panel A looks at firms head-quartered in Europe, while Panel B looks at firms head-quartered in the USA. According to Sustainalytics, the Carbon Risk score capture the remaining unmanaged carbon risk after taking into account a firm's carbon risk management activities (for details, see Morningstar, 2018b). Morningstar uses the firm-level Carbon Risk scores from Sustainalytics to compute the value-weighted fund-level Carbon Risk scores.

Panel A: Europe

	N	min	p25	mean	p50	p75	max	sd
Energy	34	8.89	16.90	28.31	26.46	35.97	62.89	14.14
Materials	74	1.59	11.63	18.33	17.33	24.54	48.40	8.02
Industrials	170	0.00	6.51	13.92	13.70	21.90	36.05	9.26
Consumer discretionary	108	0.00	0.00	8.51	7.23	12.13	41.25	7.93
Consumer staples	51	0.00	3.89	8.42	6.97	12.01	20.69	5.62
Health Care	65	0.00	0.00	2.72	0.00	5.93	14.72	4.49
Financials	144	0.00	7.95	11.70	11.86	15.27	25.20	5.27
IT	62	0.00	0.00	3.21	0.00	5.92	23.91	5.14
Communication	62	0.00	0.00	5.39	3.49	9.40	19.36	6.22
Utilities	41	0.00	8.50	15.80	14.00	23.54	38.70	9.64
Real Estate	67	4.28	8.44	12.68	12.54	17.13	20.70	4.92
Total	878	0.00	4.61	11.30	10.32	15.96	62.89	9.34

Panel B: USA

	N	min	p25	mean	p50	p75	max	sd
Energy	106	0.00	12.27	33.61	24.07	58.15	75.28	24.24
Materials	104	0.00	9.93	16.40	15.35	21.64	63.51	11.59
Industrials	149	0.00	8.27	14.84	14.21	21.16	46.22	9.56
Consumer discretionary	131	0.00	0.00	11.58	10.10	17.63	67.65	11.22
Consumer staples	60	0.00	4.74	12.03	10.64	17.50	58.06	10.08
Health care	95	0.00	0.00	8.97	7.28	14.37	81.09	11.08
Financials	161	0.00	7.24	13.03	12.98	16.25	76.20	10.19
IT	125	0.00	0.00	9.95	7.81	14.41	67.32	12.06
Communication	58	0.00	0.00	8.95	7.62	14.78	35.07	8.69
Utilities	52	0.00	9.67	16.27	16.48	23.14	37.79	10.26
Real Estate	104	0.00	8.73	13.92	13.80	18.72	54.08	8.76
Total	1,145	0.00	5.78	14.61	12.55	19.50	81.09	13.98

Table A2: Correlations between variables
This table shows the correlations between variables for the period from April 2017 through September 2019. * indicates that the parameter estimate is significantly different from zero at the 1% level.

Variables	1	2	3	4	5	6	7	8	9	10
1. LCD										
2. Flows	0.01*									
3. Normalized flows	0.02*	0.75*								
4. Return	0.04*	0.06*	-0.03*							
5. Log assets	0.08*	-0.01*	-0.01*	0.03*						
6. Volatility	0.19*	-0.05*	-0.02*	0.04*	-0.00					
7. Age	0.07*	-0.11*	-0.14*	0.01*	0.29*	0.05*				
8. Globes	0.09*	-0.00	0.00	0.01*	-0.02*	-0.08*	0.03*			
9. Stars	0.06*	0.14*	0.17*	0.04*	0.31*	-0.06*	0.00	-0.02*		
10. Socially conscious	0.11*	0.03*	0.04*	0.01*	0.05*	0.03*	-0.03*	0.17*	0.04*	
11. Institutional	-0.03*	0.03*	0.06*	0.00	0.15*	-0.02*	-0.12*	-0.04*	0.12*	0.05*

Table A3: Financial and climate performance

This table shows results of cross-sectional OLS regressions of funds' average performance (alpha) relative to the Fama-French three factor model over the period from December 2016 through April 2018 on the Low Carbon Designation (LCD) and underlying criteria, controlling for fund size and category. The sample includes funds included in our sample as of May 2018.The fund-specific Fama-French three factor models are estimated based on EU and US factors retrieved from Kenneth French's website. t-statistics based on robust standard errors are reported in parentheses. ***, **, and * indicate that the parameter estimate is significantly different from zero at the 1%, 5%, and 10% level, respectively.

	Full sample		Europe		USA	
	(1)	(2)	(3)	(4)	(5)	(6)
Dep. variable:	Fama-French 3-factor model alpha					
LCD	0.09***	0.15***	0.01	0.12***	0.26***	0.07**
	(7.94)	(9.14)	(1.04)	(6.76)	(12.59)	(2.33)
CR		-0.00		0.01***		-0.04***
		(-0.19)		(3.02)		(-6.67)
FFI		0.01***		0.01***		-0.00*
		(5.56)		(6.88)		(-1.69)
Log assets	0.02***	0.02***	0.03***	0.03***	0.01***	0.01***
	(9.70)	(7.26)	(9.37)	(6.74)	(3.54)	(3.17)
Constant	-0.33***	-0.33***	-0.31***	-0.40***	-0.53***	-0.03
	(-7.14)	(-5.37)	(-4.70)	(-5.12)	(-7.86)	(-0.36)
Observations	13,024	8,968	8,940	6,272	4,082	2,694
R-squared	0.36	0.40	0.27	0.32	0.05	0.17
Category FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes

Table A4: Cross-sectional heterogeneity of LCD flow premium: Low vs. high sustainability funds

This table shows results of OLS regressions of monthly flows from April 2017 through December 2018 exploring the differential effect of the LCD in the subsamples of low (1 or 2 Morningstar sustainability globes) and high (4 or 5 Globes). The regressions control for month-by-style and country fixed effects. t-statistics, based on robust standard errors clustered at the month and category level, are reported in parentheses. ***, **, and * indicate that the parameter estimate is significantly different from zero at the 1%, 5%, and 10% level, respectively.

	Full sample		Europe		USA	
	(1)	(2)	(3)	(4)	(5)	(6)
Dep. variable:	Flows		Flows		Flows	
	Low sust.	High sust.	Low sust.	High sust.	Low sust.	High sust.
LCD × Post	0.34**	0.09	0.30*	0.11	0.33	0.21
	(2.49)	(0.68)	(2.00)	(0.71)	(1.46)	(1.19)
LCD	0.11	0.26***	0.07	0.30***	0.20	0.02
	(0.65)	(3.43)	(0.35)	(3.97)	(1.14)	(0.20)
Observations	59,246	62,274	39,977	42,512	19,265	19,744
R-squared	0.16	0.16	0.20	0.21	0.10	0.08
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Month-style FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Month-style clustered SE	Yes	Yes	Yes	Yes	Yes	Yes

Table A5: Investors prefer low-carbon funds - Robustness check: Adding fund fixed effects

This table shows results of OLS difference-in-differences (DID) regressions of monthly flows from April 2017 through December 2018 on Low Carbon Designation (LCD), the interaction of this variable with a dummy Post equal to 1 for months following April 2018 (publication period), and control variables. Models (1), (3) and (5) use monthly net flows as the dependent variable, while models (2), (4), and (6) use monthly normalized flows. All regressions control for month-by-style and fund fixed effects. Singleton observations are dropped. t-statistics, based on robust standard errors clustered at the style and month level, are reported in parentheses. ***, **, and * indicate that the parameter estimate is significantly different from zero at the 1%, 5%, and 10% level, respectively.

	Full sample		Europe		USA	
	(1)	(2)	(3)	(4)	(5)	(6)
Dep. variable:	Flows	Normalized flows	Flows	Normalized flows	Flows	Normalized flows
LCD × Post	0.41***	2.77***	0.45***	3.11***	0.35***	2.28**
	(5.59)	(3.40)	(3.47)	(3.13)	(3.47)	(2.21)
Observations	261,361	261,361	178,267	178,267	83,087	83,087
R-squared	0.37	0.39	0.39	0.35	0.38	0.56
Constant & controls	Yes	Yes	Yes	Yes	Yes	Yes
Month-style FE	Yes	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes
Month-style clustered SE	Yes	Yes	Yes	Yes	Yes	Yes

Table A6: Investors prefer low-carbon funds - Robustness check: Fully interacted model

This table shows results of difference-in-differences regressions of monthly flows from April 2017 through December 2018 on Low Carbon Designation (LCD), control variables (monthly return, volatility, log asset, age, Δ1 Globe, Δ5 Globes, ΔStars), and the interaction of all variables with a dummy Post equal to 1 for months after April 2018. t-statistics, based on robust standard errors clustered at month level, are reported in parentheses. ***, **, and * indicate that the parameter estimate is significantly different from zero at the 1%, 5%, and 10% level, respectively.

	Full sample		Europe		USA	
	(1)	(2)	(3)	(4)	(5)	(6)
Dep. variable:	Flows	Normalized flows	Flows	Normalized flows	Flows	Normalized flows
LCD × Post	0.20**	1.98**	0.25***	2.43**	0.16*	1.66***
	(2.37)	(2.21)	(2.93)	(2.19)	(2.02)	(3.53)
LCD	0.12	0.79	0.08	0.62	0.12	0.43
	(1.03)	(0.92)	(0.62)	(0.67)	(0.96)	(0.46)
Return × Post	-0.07	-0.30	-0.04	0.20	0.02	0.08
	(-1.09)	(-0.43)	(-0.75)	(0.34)	(0.23)	(0.19)
Log assets × Post	0.06*	-0.37	-0.02	-1.01*	0.06**	-0.66
	(1.93)	(-0.94)	(-0.68)	(-1.77)	(2.38)	(-1.11)
Volatility × Post	0.22	1.91*	0.23	2.14**	0.31**	2.66*
	(1.67)	(1.92)	(1.56)	(2.15)	(2.67)	(1.76)
Age × Post	0.02***	0.05	0.02**	0.02	0.01	0.06
	(3.46)	(1.21)	(2.39)	(0.33)	(1.43)	(0.88)
Δ1 Globe × Post	-0.12	-0.59	-0.05	-0.22	-0.17	-0.32
	(-0.81)	(-0.71)	(-0.35)	(-0.24)	(-1.14)	(-0.27)
Δ5 Globes × Post	0.12	1.12	0.03	0.86	0.17	0.33
	(0.97)	(1.04)	(0.30)	(0.87)	(0.85)	(0.20)
ΔStars × Post	0.02	0.05	0.04	0.03	0.01	0.05
	(0.46)	(0.12)	(0.76)	(0.06)	(0.11)	(0.09)
Observations	261,361	261,361	178,267	178,267	83,087	83,087
R-squared	0.17	0.14	0.22	0.13	0.09	0.25
Month-style FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Month-style clustered SE	Yes	Yes	Yes	Yes	Yes	Yes

Table A7: Investors prefer low-carbon funds - Robustness check: Asset-weighted regressions

This table shows results of OLS asset-weighted difference-in-differences (DID) regressions of monthly flows from April 2017 through December 2018 on Low Carbon Designation (LCD), the interaction of this variable with a dummy Post equal to 1 for months following April 2018 (publication period), and control variables. All regressions control for month-by-style and country fixed effects. t-statistics, based on robust standard errors clustered at month level, are reported in parentheses. ***, **, and * indicate that the parameter estimate is significantly different from zero at the 1%, 5%, and 10% level, respectively.

	Full sample		Europe		USA	
	(1)	(2)	(3)	(4)	(5)	(6)
Dep. variable:	Flows	Normalized flows	Flows	Normalized flows	Flows	Normalized flows
LCD × Post	0.23***	2.08***	0.28***	2.46***	0.22**	1.96***
	(3.18)	(3.42)	(3.47)	(3.33)	(2.40)	(3.42)
LCD	0.11***	0.77**	0.08*	0.73*	0.07	0.03
	(3.03)	(2.32)	(1.92)	(1.98)	(1.08)	(0.05)
Observations	261,361	261,361	178,267	178,267	83,094	83,094
R-squared	0.17	0.14	0.22	0.13	0.08	0.24
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Month-style FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Month-style clustered SE	Yes	Yes	Yes	Yes	Yes	Yes

Table A8: Investors prefer low-carbon funds - Robustness check: Controlling for CR and FFI

This table shows results of OLS difference-in-differences (DID) regressions of monthly flows from April 2017 through December 2018 on Low Carbon Designation (LCD), Portfolio Carbon Risk (CR) and Fossil fuel involvement (FFI), their interaction with Post, and control variables (monthly return, volatility, log asset, age, $\Delta 1$ Globe, $\Delta 5$ Globes, ΔStars). All regressions control for month-by-style and country fixed effects. t-statistics, based on robust standard errors clustered at the month and categorymonth level, are reported in parentheses. ***, **, and * indicate that the parameter estimate is significantly different from zero at the 1%, 5%, and 10% level, respectively.

	Full sample		Europe		USA	
	(1)	(2)	(3)	(4)	(5)	(6)
Dep. variable:	Flows	Normalized flows	Flows	Normalized flows	Flows	Normalized flows
LCD × Post	0.23**	1.91**	0.22	1.92*	0.19*	1.06
	(2.72)	(2.84)	(1.67)	(1.86)	(1.93)	(1.68)
LCD	-0.06	-0.77	-0.06	-0.51	-0.04	-1.00*
	(-0.80)	(-1.32)	(-0.59)	(-0.70)	(-0.45)	(-1.91)
CR	-0.02	-0.20	0.00	-0.06	-0.04	-0.19
	(-0.98)	(-1.27)	(0.03)	(-0.36)	(-1.21)	(-0.71)
CR × Post	0.01	0.11	-0.00	0.00	-0.01	-0.14
	(0.29)	(0.50)	(-0.12)	(0.02)	(-0.43)	(-0.52)
FFI	-0.03***	-0.20***	-0.03***	-0.23***	-0.01	-0.11
	(-3.21)	(-3.25)	(-4.94)	(-3.63)	(-0.30)	(-0.62)
FFI × Post	0.01	0.00	0.01	0.01	0.01	0.01
	(1.55)	(0.11)	(1.13)	(0.11)	(0.84)	(0.12)
Observations	168,821	168,821	115,575	115,575	53,227	53,227
R-squared	0.16	0.14	0.20	0.13	0.10	0.27
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Month-style FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Month-style clustered SE	Yes	Yes	Yes	Yes	Yes	Yes

Table A9: Funds tilt portfolios towards low-carbon firms - Robustness checks
This table shows robustness tests to the mutual fund responses regressions. Panel A shows results of asset-weighted OLS difference-in-differences (DID) regressions of quarterly Abnormal Carbon Risk (Abn CR) and Fossil Fuel Involvement (Abn FFI) from March 2017 through September 2019 on Not Low Carbon Designation (NotLCD),the interaction of this variable with a dummy Post equal to 1 for months following April 2018 (publication period), and control variables. Panel B shows results of OLS difference-in-differences (DID) regressions using the same dependent and independent variables but adding fund fixed effects. Abnormal climate performance metrics (indicated by Abn) are constructed to account for price changes by subtracting for each category-month pair the mean CR and FFI of explicit indexers and passive investors (Active Share $\leq$60%). We compute the means separately by the degree to which the treatment criteria are fulfilled, i.e., $\varnothing$CR$\leq$10, $\varnothing$FFI$\leq$7, both, and none. All regressions control for lagged fund-level controls. Regressions in Panel A also control for quarter-by-style and country fixed effects. Those in Panel B include fund and quarter fixed effects. Singleton observations are dropped. t-statistics, based on robust standard errors clustered at the quarter and style are reported in parentheses. ***, **, and * indicate that the parameter estimate is significantly different from zero at the 1%, 5%, and 10% level, respectively.

Panel A: Asset-weighted regressions

Dep. variable:	(1) Abn CR	(2) Abn FFI
NotLCD × Post	-0.34*	-0.92**
	(-1.97)	(-2.31)
NotLCD	0.41***	0.38
	(2.97)	(1.28)
Observations	59,253	59,253
R-squared	0.12	0.09
Controls	Yes	Yes
Quarter-style FE	Yes	Yes
Country FE	Yes	Yes
Quarter-style clustered FE	Yes	Yes

Panel B: Fund fixed effects

Dep. variable:	(1) Abn CR	(2) Abn FFI
NotLCD × Post	-0.20**	-0.48**
	(-3.16)	(-2.33)
Observations	59,149	59,149
R-squared	0.85	0.78
Controls	Yes	Yes
Quarter FE	Yes	Yes
Fund FE	Yes	Yes
Quarter-style clustered FE	Yes	Yes

Can asset managers attract assets by disclosing superior ESG practices?*

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June 14, 2021

Abstract

We examine institutional investor's ESG disclosure. Using fund-level data, we find that investors reward institutional investors' positive ESG disclosure. After joining the Principles for Responsible Investing (PRI), the world's largest responsible investment network, investors are obligated to file an annual ESG report, which is assessed and scored by the PRI. Studying this private data, we find that clients reward institutions that receive higher scores on the reporting framework. We also find that this reward is particularly strong when the voluntary disclosure is confirmed by ESG ratings verified by Morningstar. Overall, these results show that by using a standardized reporting and assessment framework, clients are able to identify investors with higher levels of ESG integration, thereby partially alleviating informational asymmetries within the responsible investment landscape.

JEL Classifications: G23, G4, M41.
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1 Introduction

Environmental, Social, and Governance (ESG) reporting is receiving attention from both policymakers (EU, 2019) and practitioners (Krueger, Sautner, and Starks, 2020). The reasoning is that an efficient disclosure regime enables participants in the financial markets to correctly price risks and opportunities arising from sustainability concerns, such as human rights, gender diversity, or climate change. Recently, some progress has been made towards improving the reporting environment, with more and more countries adopting mandatory ESG disclosure rules for corporations.[1] For example, in the U.K., publicly listed companies have to disclose their CO_2 emissions, while many more do so voluntarily. Also, U.S. policymakers are debating whether to oblige companies to disclose their exposure to climate-related risks as part of the Climate Risk Disclosure Act of 2019.

A growing strand of literature studies the effects of ESG disclosure of *corporations* (Christensen, Hail, and Leuz, 2019). Corporate disclosure plays a role in enabling efficient financial markets, e.g., by decreasing informational asymmetries between market participants (Jensen and Meckling, 1976).[2]

However, to date there is almost no evidence on the ESG disclosure practices of *institutional investors*. This is surprising because the investor-client relation is subject to similar information asymmetries as the corporation-shareholder relation (Bebchuk, Cohen, and Hirst, 2017). We take a first step towards filling this gap by addressing the following questions: Do fund families disclose information about their ESG practices and processes? If so, do responsible asset owners move assets to fund families that self-report superior ESG practices? And do these fund families live up to their promises? Finally, how does the

[1] For an overview of these rules see the Carrots & Sticks 2020 report, available at `https://www.carrotsandsticks.net/media/zirbzabv/carrots-and-sticks-2020-interactive.pdf`.

[2] Recent empirical studies confirm that mandatory corporate ESG disclosure, not only improves the firm's informational environment (Krueger, Sautner, Yongjun Tang, and Zhong, 2021), but also increases firm-level innovation and the environmental performance of firms (Jouvenot and Krueger, 2020; Gibbons, 2020), even for those firms that were already disclosing ESG information voluntarily (Grewal, 2021). On the other hand, there is evidence that ESG disclosure increases the disagreement among ESG ratings (Christensen et al., 2019).

voluntary ESG disclosure of investors interact with verified measures of ESG performance, such as Morningstar's sustainability ratings or "Globes"?

A prior, it is not clear whether investors' voluntary ESG disclosure can help to attract flows from responsible clients. On the one hand, investor disclosure can alleviate the informational asymmetry problem that responsible clients face when they search for an investment manager with better ESG practices. In this view, voluntary disclosure could be an important tool for responsible financial intermediaries to signal better ESG practices. On the other hand, market participants may discount voluntary disclosure when it is difficult to verify it (Spence, 1973). These concerns are highlighted by previous evidence that institutional investors have high incentives to "greenwash", meaning to commit to responsible initiatives, but not implementing their promises (Gibson, Glossner, Krueger, Matos, and Steffen, 2021).

Differentiating between these hypotheses is important because institutional investors are in the unique position of being able to influence the behavior of corporations, nudging them towards improving their environmental and social performance (Akey and Appel, 2019; Dimson, Karakaş, and Li, 2015, 2020; Dyck, Lins, Roth, and Wagner, 2018). Directing assets towards institutions that have leading sustainability practices is a necessary step towards achieving a smooth transition to a low-carbon, more equal, and in general more sustainable economy.

This paper aims to fill this gap in the literature by examining how voluntary but standardized ESG disclosure of mutual fund families impacts fund flows. We exploit a unique institutional setting, where asset managers commit to adopt ESG practices in their organization by voluntarily joining the Principles for Responsible Investments (PRI).[3] Importantly, as part of their commitment, starting from 2014, all signatories must fill-in a yearly survey called the "Reporting & Assessment (R&A)" framework. Signatories report on their approach to integrate sustainability issues in their investment process, including but not limited to stock selection and investor engagement, compensation of executives, appoint-

[3] To date, over 3,000 institutional investors, representing nearly 60% of the global private capital market space have joined the PRI (and are so-called "*signatories*").

ment of portfolio mangers, and organizational ESG resources. In total, the survey covers over 200 indicators among 12 different modules. These survey responses are then assessed by the PRI and given scores from a maximum of A+ to a minimum of E. Higher scores are given to institutions with better ESG practices. These scores are private and shared voluntarily by the institutions themselves. Signatories generally see receiving high scores as a good outcome and are well known for advertising publicly via press releases, in their annual statements, on their websites, and via social media, when they receive high PRI scores. Moreover, the eVestment database, the largest information source for institutional investors in the U.S., also disclosed the assessment scores of signatories.

The Reporting & Assessment framework offers three unique advantages: First, the survey provides ESG investor disclosure on a comprehensive set of institutional investors given that the PRI is the largest investor initiative in the world and its signatories manage over US-$ 100 trillion assets in total.[4] Second, the survey is standardized and provides assessments that are directly comparable across institutions. This lays in stark contrast to the existing sustainability reports that cover different information for every institution. Third, every signatory of the PRI is required to fill-in the survey, even when they have dismal ESG practices, which alleviates selection bias concerns.[5] Taken together, these features enable us to run a comprehensive study of the effects of institutional investors' disclosure practices.

We start by testing if mutual fund investors reward institution that join the PRI. It is likely that merely joining is not a strong enough signal to elicit a positive response from investors. While signatories commit to uphold the PRI principles, e.g., to incorporate ESG issues into investment analysis and ownership policies, this commitment is not directly enforced by the PRI and can be seen by market participants as cheap talk (Gibson et al., 2021). Indeed, in a difference-in-differences (DiD) setting we find that joining the PRI alone does not boost fund inflow by a significant amount.

[4]See https://www.unpri.org/pri/about-the-pri.

[5]It is important to note that while every signatory is required to fill-in the survey, the decision to commit to the PRI initiative is voluntary. We discuss this below in detail.

We next examine if fund investors reward institutions that – in addition to joining the PRI – disclose superior ESG practices in the Reporting & Assessment framework, i.e., when the signatory receives a high assessment score by the PRI. Our findings indicate that this is indeed the case. After controlling for fund characteristics like size and performance, as well as fund-family and time fixed effects, obtaining an average score of A or greater in the framework relates to monthly flows that are 23 basis points (bp) higher compared to funds of institutions with no rating or that are not signatories. This is an economically important boost that translates in an average annual inflow of 15 USD million per signatory. Crucially, this holds even when we control for the funds' portfolio ESG footprints, suggesting that the better flows stem from the *disclosure* of better ESG practices rather than from differences in allocation strategies. This effect is concentrated in the institutional share classes, pointing out that only these types of investors value the additional disclosure. This is not surprising, since retail investors are usually influenced by more easy-to-access information like the Morningstar ESG rating of a fund (Hartzmark and Sussman, 2019) or by classification as "socially conscious" investment (Riedl and Smeets, 2017).[6] Institutional investors on the other hand are more likely to take into account and react to additional disclosures (Iliev, Kalodimos, and Lowry, 2020).

One potential concern is that, while every PRI signatory has to report on their ESG practices since 2014, joining the PRI is a voluntary decision by the institutional investor. Our main specification is designed with this concern in mind and includes fund family fixed effects to account for time-fixed differences in the institutions' ESG practices. Put differently, we estimate the difference in flows that an investor receives after having obtained high R&A scores to the difference in flows that the control group (signatories with no R&A scores and non-PRI) receives. To account for unobserved heterogeneity as much as possible, we further control for style-times-time fixed effects and time-varying fund-level controls.

For better identification, we next exploit the fact that the Reporting & Assessment

[6]We test the interaction between investor ESG disclosure and these alternative ESG measures later.

framework is mandatory for PRI signatories but was only introduced in 2014 and announced one year earlier. In this tighter specification, we restrict the sample to funds that joined the PRI before 2013, that is, before the R&A framework was introduced, and compare those to signatories that never joined the PRI in a difference-in-difference setting. Funds that joined before 2013 were not aware that joining the PRI will be related to extensive ESG reporting, which alleviates the selection problem. The effect of obtaining a high R&A score is, if anything, even stronger in this specification. In our most conservative test, we include fund and category-by-month fixed effects. This essentially compares the flows for the same fund before the R&A was introduced with the flows after the fund starts receiving the first batch of scores, evaluated against the flows of investors that are not part of the PRI initative. Signatories that joined PRI before 2013, experience the strongest boost in flows of 40bp per month from having an average assessment score of A or above.

Our second main result studies the interplay between the information contained in the self-disclosed Reporting & Assessment score and the sustainability rating (ESG "Globes") that a mutual fund receives from Morningstar. Investors may treat these two ESG information as substitutes, even though the R&A score has a much broader scope than the Morningstar ESG Globes, which are based on asset allocation choices alone. Alternatively, investors might only reward funds that have a strong performance on both scales, treating the two attributes as complements. This would support the "confirmation hypothesis" (Ball, Jayaraman, and Shivakumar, 2012), i.e., voluntary disclosure becomes more credible once it is "confirmed" by additional disclosure that is externally verified.

We find evidence supporting the complements hypothesis: Mutual funds of signatories that have both a high R&A score *and* the highest number of "Globes" receive an extra boost in flows of 39bp per month (6.3% of a standard deviation) from institutional share classes. This is almost twice the effect of receiving the high R&A score alone. Moreover, having a positive assessment from PRI does not mitigate the negative effect of receiving a poor Globe rating.

Are the higher flows that high-scoring PRI signatories receive warranted? That is, do fund families with better R&A scores actually have better ESG practices? In the last section of our paper, we run preliminary tests aimed at answering these questions. First, we examine whether better R&A scores correlate with more capital allocated towards companies with better ESG performance. Our findings suggest that this seems to be the case: Funds that have an average R&A score of A or better have a Morningstar portfolio ESG score that is 0.36 larger than that of the other funds (5% of a standard deviation). Moreover, it seems that filing the Reporting & Assessment itself correlates with an improvement in the ESG score, but only after the Morningstar fund sustainability score became publicly available in 2016. Second, we examine mutual funds' voting but find no significant differences between funds with high and low R&A scores. Funds of institutions that receive high assessment scores are not more likely to vote in favor of environmental and social proposals, nor do they change their behavior after they start receiving assessment scores. We caution against putting excessive weight on these results however, as these tests are run only with US-domiciled funds for which Morningstar provides voting information.

Taken together, our findings document the value of disclosing information about superior ESG practices by investment managers. As this information is not readily available, e.g., as a label in the Morningstar web portal, and not as widely processed as annual reports, only sophisticated, institutional investors react to such disclosure. Far from existing in a vacuum, the disclosure of holistic information is particularly powerful in attracting fund inflows when combined with a strong and verifiable sustainability rating from Morningstar. This speaks to the complementarity of both voluntary investor disclosure and mandatory third-party ratings as well as holistic and specific ESG measures. Finally, the assessment ratings themselves appear to correlate with a better sustainability footprint of mutual funds. It seems that, at least to some extent, PRI signatories that receive a high assessment score indeed implemented better ESG practices.

Our paper primarily contributes to the literature on the role of non-financial disclosure.

A number of papers have already analyzed the implications of such disclosure *at the corporate level*. For instance, Dhaliwal, Li, Tsang, and Yang (2011) show that voluntary ESG corporate disclosure reduces firms' cost of capital. When looking at the financial market reaction, Grewal, Riedl, and Serafeim (2019) and Griffin, Lont, and Sun (2017) find that there is a negative abnormal return following non-financial corporate disclosures, less so if the disclosure is better. Jouvenot and Krueger (2020) shows that mandating the disclosure of greenhouse-gas emissions improves firms' climate performance, even for those firms that were already disclosing this information voluntarily (Grewal, 2021). Our paper adds by providing evidence on the non-financial ESG disclosure *at the institutional investor level*. We demonstrate that investor ESG disclosure can attract responsible flows from mutual fund investors, and that it correlates with better portfolio fund scores. This implies that investor ESG disclosure is a viable signal for better ESG practices and helps to reduce ESG-related information asymmetries between institutional investors and their clients.

We also contribute to the growing number of papers that investigate signatories of the Principles for Responsible Investing. Gibson et al. (2021) ask whether PRI signatories engage in "greenwashing" and show that, at least outside of the US, signatories appear to have better ESG portfolio scores. Humphrey and Li (2021) argues that PRI signatories reduce the emissions of their portfolios. Kim and Yoon (2020) find that funds by PRI signatories domiciled in the US do not exhibit better ESG performance. Liang, Sun, and Teo (2020) look at hedge funds that committed to the PRI and find that these underperform non-signatories. In contrast to these papers, we have obtained access to the full Reporting & Assessment dataset from PRI, which enables us to study the effect of ESG investor disclosure on fund flows. We contribute by looking beyond joining PRI as a signal of ESG commitments. What matters to fund investors seems not to be joining by itself, but rather whether institutions report better ESG practices and receive better R&A assessment scores.

The remainder of the paper is structured as follows. Section 2 provides more details on the institutional setting. Section 3 describes the data. Section 4 shows the main results of the paper and Section 5 concludes.

2 Institutional setting

In 2006, a group of large institutional investors were invited by Kofi Annan, the then UN Secretary-General, to form the Principles of Responsible Investments (PRI). This group was meant to foster a sustainable financial system in order to ultimately create long-term value for investors but also for the environment and society.

Institutions that sign the Principles for Responsible Investment publicly commit to include environmental, social and governance factors in investment decision making and ownership. In 2020, over 3,000 institutional investors, representing over 100 trillion US dollars are active signatories of the Principles for Responsible Investment (PRI). These include asset owners, investment managers, and service providers. These three types of organizations apply to become a signatory by completing an application and by paying an annual fee conditional on the organization's size. Larger organizations pay higher fees, but these fees are relatively minor. The largest fee band is for investment managers with over 50$ billion US dollars of assets under management. These signatories pay an annual fee of 13,943£ or 19,000$.

Becoming a PRI signatories offers several advantages to institutional investors that seek to advance their ESG integration capabilities. For instance, PRI brings signatories together via their coordinated engagements of firms (Dimson et al., 2020), provides guidance on proxy voting, disseminates informational resources and investment tools, and organizes events.

Beyond the services provided by PRI, there are also duties that signatories have when joining the network. Starting from 2014, one of the most extensive ones is a commitment to yearly report the "activities and progress towards implementing the Principles [of Responsible Investing]" (PRI, 2020). Mandatory reporting is intended to ensure 1) accountability of the PRI and its signatories, 2) a standardized transparency tool for signatories reporting, and 3) that signatories receive feedback from which to learn and develop.

Signatories have a one-year grace period. In other words, the first reporting cycle is voluntary. Signatories that fail to report two years after joining are delisted and no longer part of the PRI. However, this is a very seldom occurrence. The reporting framework (or tool) opens on the 6th of January of each year and signatories have until the 31st of March to complete the report. This report consists of several parts or "modules", documenting the responsible investing practices of institutions across their organization. The main modules are 1) Strategy & Governance 2) Listed Equity 3) Active Ownership and 4) Asset Manager Selection, Appointment and Monitoring. Within each modules there are several types of questions: Mandatory to report and disclose, mandatory to report and voluntary to disclose, and voluntary to report and disclose. The first type of questions are published as part of the investors' transparency reports on the PRI website. The second type are published only with the signatory's consent while for the last type the signatory can opt not to answer.[7]

PRI staff then rates all the various modules of the reporting framework. Depending on the signatory's answers, a number of stars are awarded and then converted to a score that can take values from "A+" to "E". In July of each each year, investors will receive their assessment reports. While these scores are private, some signatories choose to publish them. PRI staff have informed us that high-scoring entities are likely to publicly disclose their scorecard. We also find that the eVestment database, the largest institutional investment fund product offering database in the U.S., disclosed institutional level PRI scores. However, they covered only signatories that had high scores from assessment framework. Figure 1 below shows one such example.

We are granted full access from PRI to the Reporting & Assessment survey as well as the scores that the signatories received from 2014 to 2019.

[7]As reported in PRI's website, through the reporting process, signatories can 1) evaluate their responsible investing (RI) progress against an industry-standard framework 2) receive ongoing feedback and tools for improvement 3) benchmark their performance against peers 4) strengthen internal processes and build ESG capacity 5) summarize activities for staff, clients, shareholders and regulators. For more information on the survey please consult the PRI website.

Figure 1: Example of Reporting & Assessment Scorecard


Summary Scorecard

AUM	Module Name	Your Score	Your Score / Median Score
	01.Strategy & Governance	A+	A
Indirect - Manager Sel., App. & Mon			
<10%	07. Private Equity	A+	A
Direct & Active Ownership Modules			
>50%	10. Listed Equity - Incorporation	A+	A
>50%	11. Listed Equity - Active Ownership	A+	B
<10%	12. Fixed Income - SSA	A+	B
<10%	13. Fixed Income - Corporate Financial	A+	B
10-50%	14. Fixed Income - Corporate Non-Financial	A+	B
<10%	15. Fixed Income - Securitised	Not reported	

3 Data

3.1 Mutual fund information

We start our data collection with the full list of signatories and the date when they joined the PRI. We then obtain survivorship-bias-free data (in USD) from Morningstar for all open-end equity and fixed income mutual funds that are incorporated in countries with at least one signatory. Our sample spans from January 2011 to December 2019.

Mutual funds typically issue several share classes to target different types of investors (e.g., retail and institutional clients) or geographies. However, the underlying portfolios as well as the fund management are the same across share classes. For this reason we conduct our tests at the fund level. When we aggregate data from the share class level to the fund level, we compute the returns and volatilities as the value-weighted average across different share classes. The assets under management (AuM) of a fund are the sum of the assets in the different share classes. The fund age is retrieved from the largest share class (Ceccarelli, Ramelli, and Wagner, 2020).

We define funds as "Institutional" when more than 50% of assets stem from institutional share classes.[8] We define the remaining funds as "Retail". Following Sirri and Tufano (1998), flows are computed as the monthly growth of assets under management net of reinvested returns. To ensure the robustness of our analysis, we trim flows at the 1st and 99th percentiles.

We compute the return volatility as the standard deviation of returns using a 12-month rolling window. For each fund, we also collect information on the age, global category (capturing the investment style), Morningstar's overall rating (the Morningstar "Stars", on a 1-5 scale, with 5 to indicate top financial performers), whether the fund is classified as "socially conscious",[9] and its exposure to controversial firms as well as the overall portfolio sustainability score and ESG ratings (the Morningstar "Globes", on a 1-5 scale, with 5 to indicate top sustainability performers).

To account for the impact that "Stars" have on fund flows (Del Guercio and Tkac, 2008), we define the indicators Stars upgrade and Stars downgrade. These variables take the value of one if the fund experienced an up- or downgrade in "Star" rating from the previous month. Similarly, to account for the impact of the portfolio sustainability footprint (Ammann, Bauer, Fischer, and Müller, 2019; Hartzmark and Sussman, 2019), we define the indicators $\Delta 1$ Globe and $\Delta 5$ Globes. These variables indicate funds that enter the two extreme sustainability categories (1 Globe and 5 Globes), considering the observations with continuing missing sustainability ratings as no change.[10]

Our sample consists of some 4,300 fund families that together encompass more than 53,000 funds. Table 1 below shows summary statistics for the sample at the fund-month level.

– Table 1 –

[8]Morningstar classifies as institutional the share classes that meet one of the following criteria: have the word "institutional" in the name; have a minimum initial purchase of USD 100,000 or more; specifically address institutional investors or those purchasing on a fiduciary basis, as stated in the fund prospectus.

[9]Morningstar classifies as socially conscious any fund that identifies itself as investing according to some non-financial criteria, for instance by excluding certain sectors from the investable universe, or by aiming at selectively investing in good-performing companies in terms of ESG criteria.

[10]This approach also allows us to run our tests before March 2016, when Morningstar first introduced the sustainability globes. This is a crucial aspect since most funds joined PRI well before that date.

Almost half of our sample eventually joins the PRI with 60% of the observations coming from the period after joining ("Post×PRI"). About 17% of funds are classified as institutional and 9% are classified as "socially conscious".

3.2 PRI information

In the second step of our data collection, we manually match each fund family from Morningstar to the list of PRI members. For each member we have from PRI the date of joining as well as the Reporting & Assessment scores between 2014, the first year the scores were available, and 2019. We aggregate the scores of the various modules and define ∅R&A as the average score across all available modules. Aggregation is an important step, since only signatories that receive an overall positive assessment are likely to disclose their scores.

Not all signatories fill out every module of the reporting framework, since they might not have enough exposure to a certain asset class like private equity or infrastructure investments. To account for this, we define an additional variable ∅R&A^{restr}, which is restricted to the four modules filled out by approx. 90% of signatories: Strategy & Governance, Listed Equity Screening, Integration, and Active Ownership.

The Strategy & Governance module is the most holistic part of the framework and covers the signatories' responsible investing policy. For example, one question asks how frequently objectives for responsible investments are set and reviewed. If the signatory reviews those at least onCe a year, PRI awards the maximum score for this question. The Screening, Integration, and Active Ownership are more specific modules and provide detailed information on the signatory's investment process. For example, one question asks the percentage of assets under management for which screening strategies are applied or which type of engagements (individual, collaborative, OR through service providers) the signatory undertakes.

– Table 2 –

Table 2 shows summary statistics of the PRI measures. The average assessment score is 4.22, corresponding to a score slightly above B. When we look at the restricted score, this number increases slightly to 4.61, or a score close to an A. To make interpretation of our results simpler, we define several dummies that identify signatories with an average score of A or greater (∅R&A≥A), one greater than B but smaller than A (∅R&A∈[B;A)), and one smaller than B (∅R&A<B). 27% of the sample falls in the top category, 34% is in the middle category, and 39% are in the worst category.

4 Results

4.1 Mutual fund investors value positive ESG disclosure

4.1.1 Joining the PRI

This section asks whether mutual fund investors value the disclosure of ESG information by asset managers. First, we examine if merely joining the Principles for Responsible Investing (PRI) is a strong enough signal to elicit a response from investors. When joining the PRI, asset managers commit to applying several principles to "better align investors with [the] broader objectives of society" (PRI, 2020). However, these principles should only be applied if consistent with the signatory's fiduciary duties. Moreover, they are not actively enforced by the PRI. In other words, the signal emitted by joining is not costly to the emitter and therefore not credible (Spence, 1973). Hence, it is unlikely that investors will be able to distinguish between "serious" PRI signatories and those that join only to get the "label" (Daske, Hail, Leuz, and Verdi, 2013).

We start by running the Difference-in-Differences (DID) regression below around the joining date of PRI signatories.

$$Flow_{i,t} = \alpha + \beta_1 \ Post_t \times PRI_i + \gamma' \mathbf{X_{i,t-1}} + \delta_t + \eta_i + \epsilon_{i,t} \tag{1}$$

The main explanatory variable is the difference-in-difference interaction term $Post_t \times PRI_i$. PRI_i identifies funds of asset managers that joined the PRI until the end of the sample. $Post_t$ is an indicator variable equal to 1 for the months after the asset manager became a signatory, and 0 for all prior months. $\mathbf{X_{i,t-1}}$ is a vector of time-varying lagged fund-level controls that, based on previous literature, may influence flows to funds of PRI signatories in a differential manner. These are monthly returns in the previous month, the previous year, and two years prior, the logarithm of assets under management, return volatility, the logarithm of fund's age, the fund's entrance or exit in the two extreme sustainability rating (Globes) categories, and changes of Morningstar's overall assessment of the fund (Stars).[11] δ_t represents month fixed effects and η_i fund-family fixed effects. $\epsilon_{i,t}$ is the error term. Standard errors are clustered along both month and fund-family to account for cross-sectional dependence between observations.

- Table 3 -

Table 3 above shows the regressions results. We do *not* find any significant effect of joining the PRI on fund flows, neither in the full sample (columns (1) and (2)) nor the institutional ((3) and (4)) or retail ((5) and (6)) subsamples. We confirm that this is also the case when we add the month, fund, and/or category-by-month fixed effects in Appendix Table A2.[12]

Our first set of results suggests that merely joining PRI is not a strong enough signal to warrant an investor response. One reason for this might be that investors are not able to distinguish between signatories that take the PRI principles to heart and seriously commit to implementing them, and signatories that merely join to obtain the "PRI signatory" label. Therefore, they pool all signatories in the latter, "label" category.

[11] We use changes rather than the absolute values because, as also noted in Hartzmark and Sussman (2019), if these rating systems are in equilibrium – e.g., existing investors have already sorted in low and high-sustainability funds according to their preferences, after an initial phase of reallocation – there is no reason to expect a continued flows-effect of ratings without further changes.

[12] Kim and Yoon (2020) find that US funds receive a significant boost in flows after joining the PRI. Our empirical setting is quite different from theirs, as we focus on an international sample and include a series of time-varying fund-level controls.

4.1.2 Receiving positive assessment scores

In our second battery of tests, we look at the yearly scores received by signatories that fill out the Reporting & Assessment (R&A) framework. We posit that mutual fund investors will reward signatories that receive a high overall assessment score, e.g., an average score of "A" or higher. We do not expect investors to shun away from low-scoring signatories as these will not disclose their scorecards. We test this formally by running Regression 2 below.

$$\begin{aligned} Flow_{i,t} = \alpha + \beta_1 \varnothing R\&A_{i,t-1} \geq A + \beta_2 \varnothing R\&A_{i,t-1} \in [B;A) + \beta_3 \varnothing R\&A_{i,t-1} < B + \\ + \gamma' \mathbf{X_{i,t-1}} + \delta_t + \eta_i + \epsilon_{i,t} \end{aligned} \tag{2}$$

The main explanatory variable, $\varnothing R\&A_{i,t-1} \geq A$, captures the differential inflow of funds that high-scoring signatories receive, compared to funds that have no score. Similarly, $\varnothing R\&A_{i,t-1} \in [B;A)$ and $\varnothing R\&A_{i,t-1} < B$ capture the differential inflow of funds with a medium and a low assessment scores. $\mathbf{X_{i,t-1}}, \delta_t$, and η_i are the same fund-level controls and fixed effects from Regression (1). $\epsilon_{i,t}$ is the error term and standard errors are clustered along both months and fund family.

- Table 4 -

Table 4 shows the regression results. Our main finding in column (3) shows that institutional mutual fund investors exhibit a strong liking for funds that receive a high score. Compared to funds without a score, having an average R&A rating of A or larger correlates to flows that are 23 basis points (bp), or 4% of a standard deviation, larger. This is an economically important effect, corresponding to about twice the effect from a one standard deviation increase in past month's returns.[13] In column (4), we include category-by-month fixed effects to account for changing tastes for investment strategies over time. The positive flow effect of having a high average R&A score remains robust, albeit slightly smaller. These

[13]A one standard deviation increase in monthly returns yields 3.45x0.03=0.10 percentage points – or 10bp – increase in flows.

results point out that institutional mutual fund investors attach a positive value to good ESG disclosure by asset managers.

By contrast, we find no such effect among retail investors or in the full sample (columns (1), (2), (5), and (6). This points out that only institutional investors are likely to be informed about the asset managers' disclosure contained in the R&A framework. This is consistent with prior literature that documents how institutional mutual fund investors perform better monitoring (Evans and Fahlenbrach, 2012). Moreover, since PRI is an initiative mainly organized for institutional investors, it is to be expected that the R&A framework will have higher visibility among these investors.

4.1.3 Robustness tests

One concern in our setting is that by comparing funds of PRI signatories to funds of asset managers that are not signatories, we introduce a selection bias as only ESG leading institutions will choose to join the PRI in the first place. Therefore, investors might not react to the positive disclosure embedded in the assessment scores but to some underlying characteristic of the asset manager. We consider this to be unlikely, especially given our findings from Table 3. However, in Appendix Table A3 we repeat our analysis using only funds that are PRI signatories. Our main inference remains unchanged.

Another concern could be that by taking into account modules filled out by a small fraction of signatories, we introduce a bias in the analysis. To make sure that this is not the case, in Appendix Table A4 we redefine the explanatory variables to cover only the modules that are available for the approx. 90% of signatories. Again, our findings remain unchanged.

It could be that we still have unobservable variable bias, despite already having an extensive set of fund-level controls. To account for this, we perform two additional tests: We include fund-level fixed effects in Appendix Table A5 and control for the continuous level of the funds' "Star" ratings (Del Guercio and Tkac, 2008) in Appendix Table A6. In both of these tests, our main result remains robust. Importantly, the magnitude of the coefficient of interest is very stable across the entire battery of robustness tests. This points out that we can waive the concerns mentioned in this sub-section with additional confidence.

4.1.4 Identification

While we conduct a series of robustness tests, we cannot entirely rule out endogeneity. The main concern is that if asset managers know that joining the PRI entails disclosing information about their ESG practices, only those asset managers will choose to become signatories that ex-ante were ESG leaders.

To make a causal claim, we can exploit the institutional setting of the Reporting & Assessment framework. PRI announced that it planned to introduce the survey in 2013. Thus, funds that became signatories *before 2013* did not know about the upcoming reporting requirement. This means that we can effectively treat the introduction of the R&A as an exogenous event for asset managers that became signatories in 2012 or earlier.

- Table 5 -

In Table 5 we make use of this by running Regression (2) but restrict the sample to funds that joined PRI in 2012 or earlier and those that never join. The effect of receiving a high average assessment score is even stronger in this setting. We find a boost of 17bp in the overall sample (column (1)) which is mainly concentrated in the institutional asset classes, where the boost is 40bp (column (3)). The latter coefficient is economically significant, corresponding to 6.4% of a standard deviation. These findings remain robust when controlling for category-by-month fixed effects in columns (2) and (4). We find only a marginally significant effect of receiving a high ⌀R&A rating for retail share classes.

In Appendix Table A7 we confirm that this effect is robust to a battery of additional tests: Restricting the sample to PRI funds (Panel A), using a subset of R&A modules (Panel B), including fund fixed effects (Panel C), and controlling for the continuous measure of Morningstar's performance "Stars" (Panel D). We can thus exclude for our identification test all alternative hypothesis discussed in the previous section: selection of funds into becoming PRI signatories, misrepresentation of funds that submit more assessment modules, unobservable time invariant fund-level omitted variables, and misspecification of the "Star" control variable.

Taken together, the results in this section suggest that mutual fund investors value the *positive* disclosure of ESG information by asset managers. This effect is concentrated only in institutional asset classes, consistent with institutional investors being better monitors. Moreover, a number of tests support a causal interpretation.

4.2 The interplay between the voluntary Reporting & Assessment framework and the verified ESG classification

Ball et al. (2012) demonstrate the "confirmation hypothesis", i.e., verified and voluntary disclosure are complements because through verification of outcomes the voluntarily disclosed information becomes more credible. In our setting, asset managers' decision to disclose the assessment scores is a voluntary one and the disclosed information itself is not verified.[14] Therefore, if the "confirmation hypothesis" applies to our setting, having an external verification will make the voluntary disclosure more informative.

To our knowledge there is no standardized and verified ESG disclosure framework for asset managers, with the exception of French institutional investors (Mésonnier and Nguyen, 2020). However, we can make use of the ESG portfolio ratings ("Globes") that were introduced by Morningstar in March 2016 (Hartzmark and Sussman, 2019). Obtaining the maximum number of Globes is effectively a certification by Morningstar that a mutual fund's ESG portfolio footprint is within the best 10% of funds in its investment strategy. Therefore, we expect funds of asset managers that obtain a high average assessment score *and* also have

[14]Conveniently for us, one the voluntary decision to become a signatory is made, the decision to report is no longer voluntary. The fact that assessment scores are private deters delisting of poorly performing signatories. In the spirit of Verrecchia (1983), while there is no cost of disclosing information per se, filling out the survey is costly and can be a reason why some asset managers will choose not to become signatories in the first place.

the highest number of ESG Globes will receive a particularly high reward from investors. In other words, the R&A score and the ESG Globes are complements.

Another type of voluntary disclosure present of the Morningstar platform is funds' self-classification as "socially conscious". Different from the ESG Globes, this information is self-reported by fund managers and does not represent an additional verification of a fund's commitment to ESG.[15] Thus, we expect that the R&A ratings and the socially conscious designation are *not* complements.

- Table 6 -

Table 6 tabulates the relative frequency of funds by average R&A rating and ESG Globes (Panel A) and socially conscious designation (Panel B). Interestingly, it is far from uncommon for funds of signatories that received a high average R&A score to receive only one ESG Globe: About 21% of 1 Globe funds had a high assessment score. This figure is even higher (46%) when we consider only funds that receive an assessment score in the first place. Somewhat reassuringly, funds of signatories with a high assessment score are over-represented in the 5 Globes category. 27% of funds that receive the highest ESG rating also have an average assessment score of A or higher. This figure is between 10 and 15% for funds with a lower assessment score. This leads us to conclude that different *information* is captured by the scores and the Globes.

The picture that Panel B depicts is somewhat different. Among conventional funds, the R&A ratings are very much evenly distributed. However, funds of high-scoring signatories are almost twice as likely to be "socially conscious" than funds with a medium or low assessment scores.

In Table 7 we formally test whether ESG Globes and assessment scores are complements or substitutes. To do this, we interact the main explanatory variable, $\varnothing R\&A \geq A$, with dummies for funds that receive 5 Globes and 1 Globe respectively.

[15] In the context of bond mutual funds, there is even evidence of fund managers actively miss-reporting their holdings to improve their risk-return profile (Chen, Cohen, and Gurun, 2021).

- Table 7 -

The interaction between $\varnothing R\&A \geq A$ and 5 Globes captures the additional boost in flows that funds of $\varnothing R\&A \geq A$ signatories receive when also having the highest portfolio ESG rating. We find a positive interaction effect in the full sample (columns (1) and (2)): Funds having both a high ESG rating and a high assessment score receive an additional boost in flows of 20bp. The effect is even stronger for the institutional funds where the interaction coefficient measures 42bp, almost twice the effect of having only a high assessment score. This is an economically sizable effect corresponding to a monthly boost in flows of 63bp (21bp + 42bp) or 10% of a standard deviation.

Does positive self-disclosure serve as a substitute for negative verified disclosure? In other words, can funds that receive only one ESG Globe recover part of the outflows by having a good assessment score? Our findings suggest that this is *not* the case: Funds that receive only a single Globe, and experience an outflow of about 16bp in the full sample, do not gain from receiving a high R&A score as well.

The coefficient of $\varnothing R\&A \geq A$ captures the boost in flow that high-scoring funds receive, compared to funds that have no score *and* have either no ESG rating or one that is between two and four Globes. In columns (3) and (4) we find that this coefficient is positive, significant, and very similar in magnitude to our previous results. Therefore, we can confirm our baseline result, that institutional mutual fund investors value positive ESG disclosure by asset managers.

It could be the case that the by including only the extreme Globe categories (1 and 5) we are leaving out important variation that might help explain our results. In Appendix Table A8 we include a model that is interacted with the full set of Globes. Our main finding remains robust.[16]

Taken together, these findings support the confirmation hypothesis, i.e., that verified

[16]Interestingly, after its introduction, receiving even a small number of Globes is seen negatively by investors. This suggests that from the mutual fund managers' perspective, no rating is better than a bad rating.

information (in our case the ESG Globes), complements voluntarily disclosed information (the assessment scores) making the latter more credible. The other way around does not work: Positive voluntary disclosure does not "make up" for negative but verified information.

In Table 8 we test whether the "socially conscious" designation and the assessment scores are complements or substitutes. To do this we interact the main explanatory variable, $\varnothing R\&A \geq A$, with dummies for funds that are classified by Morningstar as "socially conscious".

- Table 8 -

In columns (1) and (2) we find a positive interaction effect between our two main variable of interests. This suggests that for the average investor, having both a socially conscious designation and a high assessment score is particularly appealing. However, when we split the sample between institutional and retail clients, we find that this holds only for retail clients (columns (5) and (6)). This is surprising, as we do not expect these investors to be aware of the assessment scores in the first place. A possible explanation is that high scoring signatories market socially conscious funds more aggressively, as they see it as in line with their corporate strategy.[17]

In contrast, for institutional inventors, the interaction coefficient is insignificant. This means that while institutional investors like both socially conscious and high-assessment-score funds, they do not see these designations as complementary. This is rational, as effectively, the socially conscious designation is meant to be a holistic assessment of a funds' strategy geared towards sustainability. This is similar to what the Reporting & Assessment framework tries to capture at the asset manager level.

[17]For instance, Robeco SAM is a high-scoring signatory that offers a large number of socially conscious funds. In its homepage, Robeco claims to incorporate ESG concerns in 58 out of its 61 investment strategies. It is thus likely that through a marketing effort, such funds are simply better able to attract flows from retail investors that are particularly concerned about investing sustainably.

4.3 Are Reporting & Assessment scores cheap talk?

In the previous sections of the paper, we have shown that institutional mutual fund investors value positive ESG disclosure by asset managers, especially when this is verified by funds receiving a high ESG portfolio rating. In this section, we first ask if the boost in flows that these funds receive is warranted, that is, if asset managers live up to their promises by allocating their assets towards more sustainable firms or being more favorable towards environmental and social proxy votes. Second, we look at changes in ESG portfolio footprint and voting behavior of mutual funds. These tests speak to the "real effects" of ESG diclosure for asset managers (Eugster and Wagner, 2020; Kanodia and Sapra, 2016).[18]

4.3.1 Portfolio exposure

To test whether the R&A scores are "cheap talk", we start by running regressions of the funds' portfolio ESG Scores and the percentage of AuM in low and high controversy firms on the assessment scores indicators. Both these measures come directly from Morningstar. ESG scores are available from 2012 to September 2019, when the methodology for computing them changed. Controversy exposures are at the moment only available for US funds from 2016 to 2019. Table 9 shows the results of these regressions.

- Table 9 -

Panel A starts by comparing the levels. In column (1), we find a positive and significant relationship between having a high R&A score and the portfolio ESG score of funds. On average, funds with a higher assessment score also have larger exposure to sustainable firms. While the economic magnitude of the coefficient is relatively small (5% of a standard deviation), this result suggests that the assessment scores are not cheap talk.

[18] This is the frontier of the paper, and the current findings are still preliminary. We are currently working on matching the fund information from Morningstar with portfolio holdings from Factset. This will allow us to have a much more detailed view on the portfolio exposure of funds – not only in terms of ESG score but also in terms of exposure to incidents (Glossner, 2021) – as well as the voting records of these funds.

We find no significant differences for the controversy scores, which could be due to either our tests being underpowered or to fund managers not taking these factors into account when deciding how to allocate their assets.

Panel B looks at changes in ESG scores by introducing fund-family fixed effects in the regressions. Interestingly, in column (1), we find that fund managers do not improve their ESG score after receiving the assessment score. It is important to note that Morningstar back-filled portfolio ESG information after introducing the ESG Globes in March 2016. Before that date, the ESG exposure of funds was completely nontransparent for mutual fund investors, and potentially even to some fund managers.

To account for this, we introduce the dummy "Post Globes" in column (2) that captures the period after March 2016. After the information became easily available to investors, mutual fund managers of high-assessment-score asset managers started to improve their ESG ratings. This is consistent with existing evidence showing that transparency enhances the ESG performance of funds (Ceccarelli et al., 2020).

Concerning the exposure to controversial firms, we find a marginally significant change for funds with a high assessment score. These funds are less exposed to moderate, high, and severe controversy risk firms while having higher exposures to firms with no or a low controversy risk.

4.3.2 Proxy voting

Besides allocating funds towards more sustainable firms, fund managers can also vote in favor of environmental and social issues during the annual shareholder meetings. Arguably, an effective strategy to improve the sustainability performance of firms would be to remain invested in "laggards" and engage with them (Broccardo, Hart, and Zingales, 2020). Hence, if asset managers are not engaging in cheap talk, we expect that signatories with a high assessment score will be more supportive of environmental and social resolutions.

To test this, we obtain proxy voting data from Morningstar for the sample of US mutual funds. We compute the percentage of votes supporting Climate Change, Environment, and Other E&S (Environmental & Social) as the number of votes in support divided by the number of votes reported in Morningstar.[19]

Table 10 shows regressions of the percentage of votes cast in favor of environmental and social resolutions on the indicators for the assessment score dummies. Panel A reports regressions of levels and Panel B reports regressions of changes.

- Table 10 -

In Panel A, we find no significant differences in voting behavior between mutual funds of PRI signatories that receive a high assessment score and those that have no score. However, the coefficient on all Environmental & Social votes in column (1) is positive and economically significant: High R&A funds vote in favor of E&S resolutions 7.2 percentage points (22% of a standard deviation) more than other funds. The overall picture is the same when we look at changes in Panel B. Most coefficients are insignificant, albeit positive, leading us to believe that our tests are under-powered.

While certainly not conclusive evidence against asset managers engaging in cheap talk, this section offers reassuring findings for running future analyses using a more comprehensive voting dataset.

5 Conclusion

This paper demonstrates that the ESG disclosure of asset managers can have real consequences. Mutual funds of comparatively more ESG savvy asset managers are rewarded by their institutional clients. These effects are made possible by a mandatory and standardized reporting framework that the PRI assesses. Our results highlight that not only does a

[19]We plan to expand our dataset with voting information from Proxy Insights. Together with the portfolio holdings, this will enable us to analyze the voting behavior of mutual funds in more detail, e.g., are the funds supporting E&S proposals also when it goes against the recommendations of proxy advisers? Are mutual funds supporting E&S proposals for firms that are ex-ante more sustainable or are they targeting firms that have a larger potential for improvements?

global standardized ESG reporting framework for institutional investors exist, but that market participants are using it to guide their capital allocation decisions towards investment managers.

We also show an important interplay between voluntary and validated disclosure, where the latter confirms information present in the former. In other words, positive voluntary disclosure is complemented by externally verified information.

Preliminary findings suggest that the information contained in the Reporting & Assessment framework reflects, at least to some extent, real investment practices like portfolio allocation strategies and proxy voting. Not only that, but after signatories start receiving assessment scores, they improve their real ESG commitments, e.g., by allocating more funds to more sustainable companies. Future tests aim at better understanding this relationship.

As investment managers and asset owners continue developing their ESG integration practices, it remains to be seen how future disclosure will need to adapt to these changing investment landscapes. Objective ESG factors and other content related to non-financial reporting are difficult to standardize and therefore are expected to continuously adjust as the market develops. Therefore, this will require a continuous re-evaluation of standards, frameworks, and client-level sophistication, which can change in along with investor preferences. All these developments can influence optimal disclosure frameworks.

Overall, this study shows that clients value investor ESG integration information and use it to inform their decisions. In the future, researchers and policymakers need to better understand whether complete information is more desirable (i.e., mandatory public disclosure) or whether the current disclosure structure is more efficient to foster competition in the ESG investment field.

References

Akey, P., Appel, I., 2019. Environmental externalities of activism. Available at SSRN 3508808 .

Ammann, M., Bauer, C., Fischer, S., Müller, P., 2019. The impact of the morningstar sustainability rating on mutual fund flows. European Financial Management 25, 520–553.

Ball, R., Jayaraman, S., Shivakumar, L., 2012. Audited financial reporting and voluntary disclosure as complements: A test of the confirmation hypothesis. Journal of Accounting and Economics 53, 136–166.

Bebchuk, L. A., Cohen, A., Hirst, S., 2017. The agency problems of institutional investors. Journal of Economic Perspectives 31, 89–102.

Broccardo, E., Hart, O., Zingales, L., 2020. Exit vs. voice. Working paper .

Ceccarelli, M., Ramelli, S., Wagner, A. F., 2020. Low-carbon mutual funds. Swiss Finance Institute Research Paper .

Chen, H., Cohen, L., Gurun, U. G., 2021. Don't take their word for it: The misclassification of bond mutual funds. The Journal of Finance .

Christensen, H. B., Hail, L., Leuz, C., 2019. Adoption of CSR and sustainability reporting standards: Economic analysis and review. Working Paper .

Daske, H., Hail, L., Leuz, C., Verdi, R., 2013. Adopting a label: Heterogeneity in the economic consequences around ias/ifrs adoptions. Journal of Accounting Research 51, 495–547.

Del Guercio, D., Tkac, P. A., 2008. Star power: The effect of morningstar ratings on mutual fund flow. Journal of Financial and Quantitative Analysis 43, 907–936.

Dhaliwal, D. S., Li, O. Z., Tsang, A., Yang, Y. G., 2011. Voluntary nonfinancial disclosure and the cost of equity capital: The initiation of corporate social responsibility reporting. The Accounting Review 86, 59–100.

Dimson, E., Karakaş, O., Li, X., 2015. Active ownership. Review of Financial Studies 28, 3225–3268.

Dimson, E., Karakaş, O., Li, X., 2020. Coordinated engagements. Working paper .

Dyck, I. J. A., Lins, K. V., Roth, L., Wagner, H. F., 2018. Do institutional investors drive corporate social responsibility? International evidence. Journal of Financial Economics Forthcoming.

EU, 2019. Teg final report on climate benchmarks and benchmarks' esg disclosure. EU Technical Expert Group .

Eugster, F., Wagner, A. F., 2020. Value reporting and firm performance. Journal of International Accounting, Auditing and Taxation 40, 100319.

Evans, R. B., Fahlenbrach, R., 2012. Institutional investors and mutual fund governance: Evidence from retail–institutional fund twins. Review of Financial Studies 25, 3530–3571.

Gibbons, B., 2020. Environmental and Social Disclosure and Firm-Level Innovation.

Gibson, R., Glossner, S., Krueger, P., Matos, P., Steffen, T., 2021. Responsible institutional investing around the world. Working paper .

Glossner, S., 2021. ESG incidents and shareholder value. Working paper .

Grewal, J., 2021. Real effects of disclosure regulation on voluntary disclosers. Journal of Accounting and Economics p. 101390.

Grewal, J., Riedl, E. J., Serafeim, G., 2019. Market reaction to mandatory nonfinancial disclosure. Management Science 65, 3061–3084.

Griffin, P. A., Lont, D. H., Sun, E. Y., 2017. The relevance to investors of greenhouse gas emission disclosures. Contemporary Accounting Research 34, 1265–1297.

Hartzmark, S. M., Sussman, A. B., 2019. Do investors value sustainability? a natural experiment examining ranking and fund flows. The Journal of Finance 74, 2789–2837.

Humphrey, J. E., Li, Y., 2021. Who goes green: Reducing mutual fund emissions and its consequences. Journal of Banking & Finance 126, 106098.

Iliev, P., Kalodimos, J., Lowry, M. B., 2020. Investors' attention to corporate governance. Review of Financial Studies Forthcoming.

Jensen, M. C., Meckling, W. H., 1976. Theory of the firm: Managerial behavior, agency costs and ownership structure. Journal of Financial Economics 3, 305–360.

Jouvenot, V., Krueger, P., 2020. Mandatory corporate carbon disclosure: Evidence from a natural experiment. Working paper .

Kanodia, C., Sapra, H., 2016. A real effects perspective to accounting measurement and disclosure: Implications and insights for future research. Journal of Accounting Research 54, 623–676.

Kim, S., Yoon, A., 2020. Analyzing active managers' commitment to esg: Evidence from united nations principles for responsible investment. SSRN Electronic Journal .

Krueger, P., Sautner, Z., Starks, L. T., 2020. The importance of climate risks for institutional investors. Review of Financial Studies 33, 1067–1111.

Krueger, P., Sautner, Z., Yongjun Tang, D., Zhong, R., 2021. The Effects of Mandatory ESG Disclosure around the World.

Liang, H., Sun, L., Teo, M., 2020. Greenwashing: Evidence from hedge funds. Working paper .

Mésonnier, J.-S., Nguyen, B., 2020. Showing off cleaner hands: mandatory climate-related disclosure by financial institutions and the financing of fossil energy. Working Paper .

PRI, 2020. The six principles for responsible investment.

Riedl, A., Smeets, P., 2017. Why do investors hold socially responsible mutual funds? The Journal of Finance 72, 2505–2550.

Sirri, E. R., Tufano, P., 1998. Costly search and mutual fund flows. The Journal of Finance 53, 1589–1622.

Spence, M., 1973. Job Market Signaling. The Quarterly Journal of Economics 87, 355–374.

Verrecchia, R. E., 1983. Discretionary disclosure. Journal of accounting and economics 5, 179–194.

Tables

Table 1: Summary statistics

This table shows summary statistics of the sample variables related to the all mutual funds, both those that become PRI signatories and those that do not. The sample is at the fund-month level and covers the period from 2011 to 2019. We include all funds from countries with at least one signatory as of 2019. Mutual fund data is from Morningstar. PRI membership comes directly from the PRI. PRI is an indicator for funds that (eventually) join the PRI. Post is an indicator for the period after a fund becomes signatory. All variables are defined in Appendix Table A1.

	N	min	p25	mean	p50	p75	max	sd
PRI	3,244,621	0.00	0.00	0.60	1.00	1.00	1.00	0.49
Post× PRI	3,244,621	0.00	0.00	0.49	0.00	1.00	1.00	0.50
Flows	3,244,621	-27.39	-1.55	0.22	-0.20	0.87	57.00	6.22
Log assets$_{t-1}$	3,244,621	1.20	16.78	18.10	18.16	19.50	27.33	2.12
%AUM Inst	3,244,621	0.00	0.00	0.18	0.00	0.12	1.00	0.34
Institutional fund	3,244,621	0.00	0.00	0.17	0.00	0.00	1.00	0.38
Return$_{t-1}$	3,155,603	-9.61	-1.44	0.52	0.53	2.57	10.58	3.45
Return$_{t-12;t-1}$	2,948,106	-46.58	-2.65	5.52	4.42	13.32	92.31	12.33
Return$_{t-24;t-13}$	2,561,260	-46.58	-1.94	6.43	5.41	14.55	92.31	12.66
Stdev. ret$_{t-1}$	3,199,384	0.33	2.38	3.77	3.49	4.86	11.82	1.96
Log Fund age$_{t-1}$	3,177,669	0.04	1.47	2.06	2.16	2.72	3.53	0.82
Stars$_{t-1}$	2,193,257	1.00	2.00	3.10	3.00	4.00	5.00	1.07
Stars upgrade	2,168,377	0.00	0.00	0.07	0.00	0.00	1.00	0.25
Stars downgrade	2,168,377	0.00	0.00	0.07	0.00	0.00	1.00	0.25
Socially conscious	3,244,621	0.00	0.00	0.09	0.00	0.00	1.00	0.29
ESG Globes	591,445	1.00	2.00	3.04	3.00	4.00	5.00	1.11
Δ5Globes	3,244,621	0.00	0.00	0.00	0.00	0.00	1.00	0.07
Δ1Globes	3,244,621	0.00	0.00	0.00	0.00	0.00	1.00	0.07

Table 2: Summary statistics
This table shows summary statistics for funds that are PRI signatories and received an Reporting & Assessment (R&A) score. The sample is at the fund-year level and covers the period from 2014, when the R&A framework was introduced, to 2019. We include all funds from countries with at least one signatory as of 2019. Mutual fund data is from Morningstar. R&A scores information comes from the PRI. The score variables takes a value of 1 for the lowest score, E, and a value of 6 for the highest score, A+. The various modules that constitute the average scores are listed separately, SAM stands "Selection, Appointment, and Monitoring processes". All variables are defined in Appendix Table A1.

	N	min	p25	mean	p50	p75	max	sd
∅R&A_Score$_{t-1}$	106,185	1.25	3.50	4.22	4.25	5.00	6.00	0.95
∅R&A_Score_restricted$_{t-1}$	106,185	1.25	4.00	4.61	4.75	5.25	6.00	0.86
∅R&A$_{t-1} \geq A$	106,185	0.00	0.00	0.27	0.00	1.00	1.00	0.44
∅R&A$_{t-1} \in [B; A)$	106,185	0.00	0.00	0.34	0.00	1.00	1.00	0.47
∅R&A$_{t-1} < B$	106,185	0.00	0.00	0.39	0.00	1.00	1.00	0.49
Strategy & Governance	106,185	2.00	5.00	5.08	5.00	6.00	6.00	0.84
SAM - Listed Equity	41,332	1.00	1.00	2.74	2.00	4.00	6.00	1.52
SAM - Fixed Income	20,111	1.00	1.00	2.39	1.00	4.00	6.00	1.77
Listed Equity - Screening	89,726	1.00	4.00	4.64	5.00	5.00	6.00	1.06
Listed Equity - Integration	97,432	1.00	4.00	4.53	5.00	5.00	6.00	1.00
Active Ownership	103,063	1.00	4.00	4.22	4.00	5.00	6.00	1.09
Private Equity	19,680	1.00	1.00	2.07	2.00	2.00	6.00	1.21
Direct Property	31,753	1.00	1.00	3.18	4.00	5.00	6.00	1.68
Direct Infrastructure	14,830	1.00	2.00	3.17	2.00	5.00	6.00	1.78

Table 3: Joining the PRI - Effect on fund flows

This table shows Difference-in-Differences (DID) regressions of flows on an indicator for funds that join the PRI interacted with a dummy for the period after the fund became a signatory (Post). All regressions control for lagged fund characteristics and fund-family fixed effects. The odd columns also include month fixed effects. The even ones control for category-by-month fixed effects instead. The direct effect of the dummy Post is absorbed by the time fixed effects. The sample includes all funds from countries with a least one PRI signatory and spans from 2011 to 2019. Singleton observations are dropped. t-statistics, based on robust standard errors clustered at the fund-family and month level, are reported in parentheses. ***, **, and * indicate that the parameter estimate is significantly different from zero at the 1%, 5%, and 10% level, respectively. All variables are defined as in Appendix Table A1.

	All funds		Institutional		Retail	
	(1)	(2)	(3)	(4)	(5)	(6)
Dep. variable:	Flows	Flows	Flows	Flows	Flows	Flows
Post × PRI	-0.05	-0.02	0.02	0.06	-0.08	-0.03
	(-0.88)	(-0.32)	(0.17)	(0.57)	(-1.15)	(-0.56)
Return_{t-1}	0.06***	0.11***	0.03**	0.09***	0.06***	0.11***
	(5.72)	(10.09)	(2.46)	(5.76)	(6.09)	(9.99)
$\text{Return}_{t-12;t-1}$	0.04***	0.06***	0.03***	0.06***	0.04***	0.06***
	(17.07)	(20.55)	(9.69)	(11.46)	(16.80)	(20.12)
$\text{Return}_{t-24;t-13}$	0.01***	0.02***	0.01***	0.03***	0.01***	0.01***
	(6.00)	(10.62)	(4.30)	(8.97)	(5.78)	(8.75)
Stdev. ret_{t-1}	-0.14***	-0.10***	-0.15***	-0.09***	-0.14***	-0.10***
	(-8.99)	(-5.91)	(-7.84)	(-3.18)	(-8.18)	(-5.50)
Log assets_{t-1}	0.04***	0.04***	0.01	0.01	0.04***	0.04***
	(4.55)	(4.85)	(0.87)	(0.68)	(4.16)	(4.52)
Log Fund age_{t-1}	-0.56***	-0.56***	-0.65***	-0.62***	-0.52***	-0.53***
	(-19.44)	(-20.30)	(-11.91)	(-12.09)	(-16.84)	(-17.76)
Stars upgrade	0.02	-0.02	0.00	-0.06	0.02	-0.02
	(1.01)	(-1.47)	(0.03)	(-1.65)	(1.10)	(-0.95)
Stars downgrade	-0.10***	-0.04**	-0.11***	-0.03	-0.09***	-0.03*
	(-5.10)	(-2.07)	(-2.62)	(-0.81)	(-4.79)	(-1.95)
Δ5Globes	-0.01	0.01	0.04	0.06	-0.02	-0.01
	(-0.13)	(0.26)	(0.29)	(0.42)	(-0.36)	(-0.17)
Δ1Globes	-0.17**	-0.15**	-0.25	-0.21	-0.13*	-0.12*
	(-2.41)	(-2.17)	(-1.42)	(-1.17)	(-1.91)	(-1.77)
Constant	0.60***	0.24	1.33***	0.76**	0.50***	0.18
	(3.48)	(1.40)	(3.82)	(2.28)	(2.76)	(1.01)
Observations	1,865,535	1,865,535	367,838	367,838	1,497,229	1,497,229
R-squared	0.03	0.05	0.04	0.06	0.03	0.05
Fund-Family FE	Yes	Yes	Yes	Yes	Yes	Yes
Category-Month FE	No	Yes	No	Yes	No	Yes
Month FE	Yes	No	Yes	No	Yes	No

Table 4: R&A Ratings and fund flows
This table shows regressions of flows on indicator variables for several cutoffs of the average Reporting & Assessment (∅R&A) scores of PRI signatories. These are respectively an average score of A or greater; greater than B but less then A; and one smaller than B. These indicators are set to zero for months when no ratings are available or the fund is not a PRI signatory. All regressions control for lagged fund characteristics and fund-family fixed effects. The odd columns also include month fixed effects. The even ones control for category-by-month fixed effects instead. The sample includes all funds from countries with a least one PRI signatory and spans from 2011 to 2019. Singleton observations are dropped. t-statistics, based on robust standard errors clustered at the fund-family and month level, are reported in parentheses. ***, **, and * indicate that the parameter estimate is significantly different from zero at the 1%, 5%, and 10% level, respectively. All variables are defined as in Appendix Table A1.

	All funds		Institutional		Retail	
Dep. variable:	(1) Flows	(2) Flows	(3) Flows	(4) Flows	(5) Flows	(6) Flows
$\varnothing$R&A$_{t-1} \geq A$	0.07	0.06	0.23**	0.20**	0.03	0.01
	(1.30)	(1.12)	(2.50)	(2.31)	(0.64)	(0.34)
$\varnothing$R&A$_{t-1} \in [B; A)$	0.01	-0.03	0.03	0.01	-0.00	-0.05
	(0.18)	(-0.64)	(0.32)	(0.10)	(-0.05)	(-1.17)
$\varnothing$R&A$_{t-1} < B$	0.00	-0.01	0.03	0.04	-0.01	-0.02
	(0.04)	(-0.18)	(0.25)	(0.34)	(-0.22)	(-0.54)
Return$_{t-1}$	0.06***	0.11***	0.03**	0.09***	0.06***	0.11***
	(5.72)	(10.08)	(2.46)	(5.76)	(6.77)	(12.71)
Return$_{t-12;t-1}$	0.04***	0.06***	0.03***	0.06***	0.04***	0.06***
	(17.07)	(20.55)	(9.66)	(11.42)	(18.76)	(22.04)
Return$_{t-24;t-13}$	0.01***	0.02***	0.01***	0.03***	0.01***	0.01***
	(6.02)	(10.64)	(4.29)	(8.97)	(6.13)	(10.23)
Stdev. ret$_{t-1}$	-0.14***	-0.10***	-0.15***	-0.09***	-0.14***	-0.10***
	(-8.97)	(-5.90)	(-7.82)	(-3.16)	(-9.54)	(-6.45)
Log assets$_{t-1}$	0.04***	0.04***	0.01	0.01	0.04***	0.04***
	(4.54)	(4.84)	(0.87)	(0.68)	(5.83)	(6.28)
Log Fund age$_{t-1}$	-0.56***	-0.56***	-0.64***	-0.62***	-0.52***	-0.53***
	(-19.43)	(-20.29)	(-11.88)	(-12.02)	(-20.56)	(-21.91)
Stars upgrade	0.02	-0.02	0.00	-0.06	0.02	-0.02
	(1.01)	(-1.47)	(0.05)	(-1.65)	(1.13)	(-0.95)
Stars downgrade	-0.10***	-0.04**	-0.11**	-0.03	-0.09***	-0.03*
	(-5.10)	(-2.07)	(-2.61)	(-0.80)	(-4.76)	(-1.94)
Δ5Globes	-0.01	0.01	0.04	0.06	-0.02	-0.01
	(-0.12)	(0.26)	(0.29)	(0.42)	(-0.36)	(-0.16)
Δ1Globes	-0.16**	-0.15**	-0.25	-0.20	-0.12*	-0.12*
	(-2.39)	(-2.16)	(-1.40)	(-1.16)	(-1.84)	(-1.71)
Constant	0.56***	0.22	1.29***	0.75**	0.46***	0.17
	(3.32)	(1.34)	(3.86)	(2.34)	(3.57)	(1.26)
Observations	1,865,535	1,865,535	367,838	367,838	1,497,229	1,497,229
R-squared	0.03	0.05	0.04	0.06	0.03	0.05
Fund-Family FE	Yes	Yes	Yes	Yes	Yes	Yes
Category-Month FE	No	Yes	No	Yes	No	Yes
Month FE	Yes	No	Yes	No	Yes	No

Table 5: R&A Ratings - Identification test: Funds that joined the PRI before 2013

This table shows regressions of flows on an indicator variable for several cutoffs of the average Reporting & Assessment (∅R&A) scores of PRI signatories. These are respectively an average score of A or greater; greater than B but less then A; and one smaller than B. The sample covers only signatories that either join before 2013, when submitting an R&A report became mandatory, or funds that do *not* file such report. These indicators are set to zero for months when no ratings are available or the fund is not a PRI signatory. All regressions control for lagged fund characteristics and fund-family fixed effects. The odd columns also include month fixed effects. The even ones control for category-by-month fixed effects instead. The sample includes all funds from countries with a least one PRI signatory and spans from 2011 to 2019. Singleton observations are dropped. t-statistics, based on robust standard errors clustered at the fund-family and month level, are reported in parentheses. ***, **, and * indicate that the parameter estimate is significantly different from zero at the 1%, 5%, and 10% level, respectively. All variables are defined as in Appendix Table A1.

	All funds		Institutional		Retail	
	(1)	(2)	(3)	(4)	(5)	(6)
Dep. variable:	Flows	Flows	Flows	Flows	Flows	Flows
$\varnothing$R&A$_{t-1} \geq A$	0.17***	0.15**	0.40***	0.32***	0.12*	0.11
	(2.77)	(2.44)	(3.47)	(2.86)	(1.87)	(1.61)
$\varnothing$R&A$_{t-1} \in [B; A)$	0.07	0.01	0.19	0.12	0.04	-0.02
	(1.14)	(0.20)	(1.61)	(1.05)	(0.67)	(-0.25)
$\varnothing$R&A$_{t-1} < B$	0.09	0.05	0.18	0.14	0.07	0.04
	(1.18)	(0.78)	(1.03)	(0.83)	(0.97)	(0.55)
Observations	1,473,631	1,473,631	283,977	283,977	1,189,269	1,189,269
R-squared	0.03	0.05	0.04	0.07	0.03	0.05
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fund-Family FE	Yes	Yes	Yes	Yes	Yes	Yes
Category-Month FE	No	Yes	No	Yes	No	Yes
Month FE	Yes	No	Yes	No	Yes	No

Table 6: R&A Ratings, Sustainability Globes, and Socially conscious designation This table shows the absolute frequencies of funds along cutoffs of the average Reporting & Assessment (∅R&A) scores of PRI signatories. These are respectively an average score of A or greater; greater than B but less then A; and one smaller than B. The frequencies are reported separately along the Morningstar sustainability "Globes" ratings (Panel A) and the "Socially conscious" designation (Panel B).

Panel A: Morningstar sustainability ratings ("Globes")

∅R&A	0 (Missing)	1	2	3	4	5	Total
$\geq A$	205,548	10,964	31,688	57,696	36,561	17,345	359,802
$\in [B; A)$	243,922	6,641	20,208	33,354	20,953	9,869	334,947
$< B$	267,122	6,300	15,804	25,188	15,423	6,701	336,538
0 (Missing)	1,936,584	28,948	63,483	93,724	60,786	29,809	2,213,334
Total	2,653,176	52,853	131,183	209,962	133,723	63,724	3,244,621
% ∅R&A$\geq A$	7.75%	20.74%	24.16%	27.48%	27.34%	27.22 %	11.09%

Panel B: Socially conscious funds

∅R&A	Conventional	Socially conscious	Total
$\geq A$	297,475	62,327	359,802
$\in [B; A)$	296,396	38,551	334,947
$< B$	305,986	30,552	336,538
0 (Missing)	2,044,795	168,539	2,213,334
Total	2,944,652	299,969	3,244,621
% ∅R&A$\geq A$	10.10%	20.78%	11.09%

Table 7: R&A Ratings and ESG "Globes"

This table shows regressions of flows on an indicator variable for funds with a high average R&A score of A or greater and its interaction with an indicator for funds with five and one Morningstar ESG Globes respectively. The regressions control for funds having an ∅R&A score greater than B but less then A and for funds with a score smaller than B. The ∅R&A and Globes indicators are set to zero for months when no ratings are available or the fund is not a PRI signatory. All regressions control for lagged fund characteristics and fund-family fixed effects. The odd columns also include month fixed effects. The even ones control for category-by-month fixed effects instead. The sample includes all funds from countries with a least one PRI signatory and spans from 2011 to 2019. Singleton observations are dropped. t-statistics, based on robust standard errors clustered at the fund-family and month level, are reported in parentheses. ***, **, and * indicate that the parameter estimate is significantly different from zero at the 1%, 5%, and 10% level, respectively. All variables are defined as in Appendix Table A1.

	All funds		Institutional		Retail	
	(1)	(2)	(3)	(4)	(5)	(6)
Dep. variable:	Flows	Flows	Flows	Flows	Flows	Flows
∅R&A$_{t-1} \geq A$ × 5 Globes	0.20**	0.23***	0.42**	0.39**	0.15	0.20**
	(2.35)	(2.75)	(2.58)	(2.35)	(1.62)	(2.14)
5 Globes	-0.01	0.02	0.05	0.11	-0.03	-0.02
	(-0.13)	(0.44)	(0.45)	(1.10)	(-0.53)	(-0.39)
∅R&A$_{t-1} \geq A$ × 1 Globe	-0.05	-0.06	-0.04	-0.02	-0.04	-0.06
	(-0.50)	(-0.61)	(-0.19)	(-0.09)	(-0.37)	(-0.52)
1 Globe	-0.16***	-0.11**	-0.21*	-0.10	-0.14**	-0.11*
	(-2.82)	(-2.04)	(-1.71)	(-0.80)	(-2.39)	(-1.94)
∅R&A$_{t-1} \geq A$	0.06	0.05	0.21**	0.19**	0.02	0.01
	(1.16)	(0.95)	(2.30)	(2.10)	(0.33)	(0.09)
∅R&A$_{t-1} \in [B; A)$	0.01	-0.03	0.03	0.01	-0.00	-0.05
	(0.18)	(-0.64)	(0.33)	(0.11)	(-0.04)	(-0.91)
∅R&A$_{t-1} < B$	0.00	-0.01	0.03	0.04	-0.01	-0.02
	(0.04)	(-0.19)	(0.25)	(0.35)	(-0.16)	(-0.43)
Constant	0.56***	0.23	1.30***	0.75**	0.46**	0.17
	(3.34)	(1.34)	(3.89)	(2.36)	(2.57)	(0.95)
Observations	1,865,535	1,865,535	367,838	367,838	1,497,229	1,497,229
R-squared	0.03	0.05	0.04	0.06	0.03	0.05
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fund-Family FE	Yes	Yes	Yes	Yes	Yes	Yes
Category-Month FE	No	Yes	No	Yes	No	Yes
Month FE	Yes	No	Yes	No	Yes	No

Table 8: R&A Ratings and socially conscious funds

This table shows regressions of flows on an indicator variable for funds with a high average R&A score of A or greater and its interaction with an indicator for socially conscious funds. The regressions control for funds having an ∅R&A score greater than B but less then A and for funds with a score smaller than B. The ∅R&A indicators are set to zero for months when no ratings are available or the fund is not a PRI signatory. All regressions control for lagged fund characteristics and fund-family fixed effects. The odd columns also include month fixed effects. The even ones control for category-by-month fixed effects instead. The sample includes all funds from countries with a least one PRI signatory and spans from 2011 to 2019. Singleton observations are dropped. t-statistics, based on robust standard errors clustered at the fund-family and month level, are reported in parentheses. ***, **, and * indicate that the parameter estimate is significantly different from zero at the 1%, 5%, and 10% level, respectively. All variables are defined as in Appendix Table A1.

	All funds		Institutional		Retail	
	(1)	(2)	(3)	(4)	(5)	(6)
Dep. variable:	Flows	Flows	Flows	Flows	Flows	Flows
$\varnothing$R&A$_{t-1} \geq A \times$ Soc. cons.	0.25***	0.23***	0.09	0.11	0.30***	0.27***
	(3.27)	(3.07)	(0.69)	(0.98)	(3.59)	(3.29)
Soc. cons.	0.22***	0.23***	0.22**	0.23**	0.23***	0.24***
	(5.06)	(5.25)	(2.32)	(2.54)	(4.87)	(5.10)
$\varnothing$R&A$_{t-1} \geq A$	0.02	0.01	0.21**	0.18*	-0.02	-0.03
	(0.41)	(0.26)	(2.20)	(1.94)	(-0.38)	(-0.55)
$\varnothing$R&A$_{t-1} \in [B; A)$	0.00	-0.03	0.02	0.00	-0.01	-0.05
	(0.09)	(-0.74)	(0.28)	(0.05)	(-0.11)	(-0.99)
$\varnothing$R&A$_{t-1} < B$	-0.00	-0.01	0.03	0.04	-0.01	-0.03
	(-0.04)	(-0.25)	(0.23)	(0.33)	(-0.26)	(-0.51)
Constant	0.55***	0.21	1.29***	0.74**	0.45**	0.15
	(3.26)	(1.23)	(3.84)	(2.32)	(2.49)	(0.82)
Observations	1,865,535	1,865,535	367,838	367,838	1,497,229	1,497,229
R-squared	0.03	0.05	0.04	0.06	0.03	0.05
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fund-Family FE	Yes	Yes	Yes	Yes	Yes	Yes
Category-Month FE	No	Yes	No	Yes	No	Yes
Month FE	Yes	No	Yes	No	Yes	No

Table 9: Are R&A Ratings cheap talk? - Asset allocation
This table shows regressions of fund's ESG portfolio score (model (1)) and controversy score (models (2) to (5)) on indicator variables for several cutoffs of the average Reporting & Assessment (∅R&A) scores of PRI signatories. These are respectively an average score of A or greater; greater than B but less then A; and one smaller than B. These indicators are set to zero for months when no ratings are available or the fund is not a PRI signatory. Panel B show the interaction between the ∅R&A dummies and an indicator for the time period after March 2016, when the ESG Globes were launched ("Post Globes"). In Panel A, all regressions control for lagged fund characteristics and category-by-month fixed effects. In Panel B, all regressions also control for fund-family fixed effects. The sample includes all funds from countries with a least one PRI signatory and spans from 2012 to September 2019. The controversy score is available only for US funds. Singleton observations are dropped. t-statistics, based on robust standard errors clustered at the fund-family and month level, are reported in parentheses. ***, **, and * indicate that the parameter estimate is significantly different from zero at the 1%, 5%, and 10% level, respectively. All variables are defined as in Appendix Table A1.

Panel A: Regressions of levels

Dep. var:	ESG Score	%AUM in Firms with Controversy Score:			
	(1)	(2) Zero & Low	(3) Moderate	(4) Significant	(5) High & Severe
$\varnothing$R&A$_{t-1} \geq A$	0.36***	-0.36	-0.26	0.47	0.17
	(3.74)	(-0.68)	(-0.75)	(0.86)	(0.78)
$\varnothing$R&A$_{t-1} \in [B; A)$	0.30***	-0.92	0.23	0.62	0.14
	(3.43)	(-1.45)	(0.68)	(1.11)	(0.54)
$\varnothing$R&A$_{t-1} < B$	0.08	-0.18	0.02	0.08	0.11
	(1.02)	(-0.38)	(0.05)	(0.28)	(0.50)
Constant	50.90***	42.26***	25.97***	22.87***	6.25***
	(142.61)	(21.36)	(19.06)	(16.00)	(6.25)
Observations	652,124	96,067	96,067	96,067	96,067
R-squared	0.72	0.81	0.53	0.69	0.58
Controls	Yes	Yes	Yes	Yes	Yes
Fund-Family FE	No	No	No	No	No
Category-Month FE	Yes	Yes	Yes	Yes	Yes

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Panel B: Regressions of changes

Dep. var:	ESG Score		%AUM in Firms with Controversy Score:			
	(1)	(2)	(3) Zero & Low	(4) Moderate	(5) Significant	(6) High & Severe
$\varnothing$R&A$_{t-1} \geq A$	0.05	-0.12	0.91*	-0.46*	-0.21	-0.44**
	(0.87)	(-1.24)	(2.00)	(-1.77)	(-0.47)	(-2.62)
$\varnothing$R&A$_{t-1} \geq A \times$ Post Globes		0.21**				
		(2.01)				
$\varnothing$R&A$_{t-1} \in [B; A)$	0.04	-0.14**	0.55	-0.23	-0.17	-0.37*
	(0.76)	(-2.24)	(1.36)	(-0.95)	(-0.48)	(-1.82)
$\varnothing$R&A$_{t-1} \in [B; A) \times$ Post Globes		0.25***				
		(3.17)				
$\varnothing$R&A$_{t-1} < B$	-0.04	-0.11**	0.40	-0.04	-0.20	-0.24
	(-0.82)	(-2.19)	(0.94)	(-0.17)	(-0.55)	(-1.21)
$\varnothing$R&A$_{t-1} < B \times$ Post Globes		0.13*				
		(1.98)				
Constant	50.64***	50.63***	36.40***	26.01***	25.84***	9.21***
	(165.66)	(165.51)	(14.98)	(13.58)	(15.30)	(8.05)
Observations	652,124	652,124	96,056	96,056	96,056	96,056
R-squared	0.78	0.78	0.84	0.61	0.73	0.65
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fund-Family FE	Yes	Yes	Yes	Yes	Yes	Yes
Category-Month FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 10: Are R&A Ratings cheap talk? - Proxy Voting

This table shows regressions of fund's percentage of votes cast in support of E&S proposals on indicator variables for several cutoffs of the average Reporting & Assessment (∅R&A) scores of PRI signatories. These are respectively an average score of A or greater; greater than B but less then A; and one smaller than B. These indicators are set to zero for months when no ratings are available or the fund is not a PRI signatory. In Panel A, all regressions control for lagged fund characteristics and category-by-month fixed effects. In Panel B, all regressions also control for fund-family fixed effects. The sample includes all US-funds and spans from 2016 to 2019. Singleton observations are dropped. t-statistics, based on robust standard errors clustered at the fund-family and month level, are reported in parentheses. ***, **, and * indicate that the parameter estimate is significantly different from zero at the 1%, 5%, and 10% level, respectively. All variables are defined as in Appendix Table A1.

Panel A: Regressions of levels

Dep. var:	%Votes supporting proposals:			
	(1) All E&S	(2) Climate change	(3) Environment	(4) Other E&S
$\varnothing$R&A$_{t-1} \geq A$	7.17	6.66	9.17	-2.42
	(1.29)	(1.05)	(1.41)	(-0.52)
$\varnothing$R&A$_{t-1} \in [B; A)$	2.50	2.02	1.23	-1.05
	(0.47)	(0.33)	(0.19)	(-0.27)
$\varnothing$R&A$_{t-1} < B$	4.58	5.76	3.43	-2.40
	(0.84)	(0.92)	(0.50)	(-0.46)
Constant	124.10***	129.60***	136.95***	85.53***
	(10.10)	(9.33)	(9.09)	(6.90)
Observations	65,969	58,717	42,821	20,504
R-squared	0.10	0.10	0.09	0.13
Controls	Yes	Yes	Yes	Yes
Fund-Family FE	No	No	No	No
Category-Month FE	Yes	Yes	Yes	Yes

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Panel B: Regressions of changes

Dep. var:	%Votes supporting proposals:			
	(1) All E&S	(2) Climate change	(3) Environment	(4) Other E&S
$\varnothing$R&A$_{t-1} \geq A$	2.80	2.94	4.18	-1.22
	(1.27)	(1.36)	(1.11)	(-0.31)
$\varnothing$R&A$_{t-1} \in [B; A)$	3.39*	2.50	4.96	0.09
	(1.79)	(1.29)	(1.46)	(0.03)
$\varnothing$R&A$_{t-1} < B$	3.56*	4.55**	6.48	-6.20*
	(1.88)	(2.11)	(1.58)	(-1.86)
Constant	42.31***	41.24***	53.44***	26.69***
	(6.58)	(5.86)	(5.06)	(3.03)
Observations	65,969	58,717	42,821	20,504
R-squared	0.59	0.60	0.56	0.49
Controls	Yes	Yes	Yes	Yes
Fund-Family FE	Yes	Yes	Yes	Yes
Category-Month FE	Yes	Yes	Yes	Yes

‘

Appendix Tables

Table A1: Variable definitions

Panel A: Fund-level variables

Δ5Globes	Indicator for the month when a fund switches in the five sustainability globes category.
Δ1Globe	Indicator for the month when a fund switches in the one sustainability globe category.
5 Globes	Indicator for funds that have five sustainability globes.
1 Globe	Indicator for funds that have one sustainability globe.
Flows	The inflow of funds, net of returns, that a fund receives during a month in % of assets under management.
Institutional	Dummy for funds that have 50% or more of assets under management from institutional asset classes.
Log assets	The natural logarithm of the assets under management of a fund.
Log fund age	The natural logarithm of the number of years that passed from the incorporation date of the fund.
Post Globes	Indicator for the period after March 2016, when Morningstar introduced the ESG Globes.
Return_{t-1}	Return in the previous month.
$\text{Return}_{t-12;t-1}$	Return in the previous year.
$\text{Return}_{t-24;t-13}$	Return two years ago.
Socially conscious (Soc. cons.)	Indicator variable for funds that are classified by Morningstar as "socially conscious".
Stars downgrade	Indicator for the month when a fund looses one star.
Stars upgrade	Indicator for the month when a fund receives one additional star.
Stdev. ret	Standard deviation of monthly returns over the past twelve months.

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Panel B: PRI Reporting and Assessment Variables

PRI	Indicator for funds that eventually join the PRI.
Post × PRI	Indicator for the time period after a fund becomes a PRI signatory.
∅ R&A_Score	Average of the scores received by a fund across all Reporting and Assessment modules.
∅R&A_Score_restricted	Average of the scores received by a fund across a subset of Reporting and Assessment modules: Strategy and Governance, Listed Equity - Screening, Listed Equity - Integration, and Active Ownership.
∅R&A$_{t-1} \geq A$	Indicator variable for funds that have an average score of A or greater across all modules.
∅R&A$_{t-1} \in [B; A)$	Indicator variable for funds that have an average score of B or greater, but smaller than A across all modules.
∅R&A$_{t-1} < B$	Indicator variable for funds that have an average score smaller than B across all modules.

Table A2: Robustness test for Joining the PRI

This table shows Difference-in-Differences (DID) regressions of flows on an indicator for funds that join the PRI interacted with a dummy for the period after the fund became a signatory (Post). All regressions control for lagged fund characteristics. Columns (1), (4), and (7) include fund-family and month fixed effects. (2), (5), and (8) include fund and month fixed effects. (3), (6), and (9) include fund and category-month fixed effects. The direct effect of the dummy Post is absorbed by the time fixed effects. The sample includes all funds from countries with a least one PRI signatory and spans from 2011 to 2019. Singleton observations are dropped. t-statistics, based on robust standard errors clustered at the fund-family and month level, are reported in parentheses. ***, **, and * indicate that the parameter estimate is significantly different from zero at the 1%, 5%, and 10% level, respectively. All variables are defined as in Appendix Table **??**.

	All funds			Institutional			Retail		
	(1) Flows	(2) Flows	(3) Flows	(4) Flows	(5) Flows	(6) Flows	(7) Flows	(8) Flows	(9) Flows
Post × PRI	-0.05	-0.03	-0.00	0.02	0.07	0.09	-0.08	-0.06	-0.02
	(-0.89)	(-0.55)	(-0.03)	(0.18)	(0.64)	(0.97)	(-1.16)	(-0.85)	(-0.37)
Constant	0.60***	9.35***	9.28***	1.33***	12.51***	12.05***	0.51***	9.58***	9.75***
	(3.51)	(12.54)	(12.32)	(3.84)	(12.07)	(11.63)	(2.80)	(10.65)	(10.52)
Observations	1,865,112	1,865,112	1,865,112	367,696	367,696	367,696	1,496,802	1,496,802	1,496,802
R-squared	0.03	0.10	0.11	0.04	0.11	0.13	0.03	0.11	0.12
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund-Family FE	Yes	No	No	Yes	No	No	Yes	No	No
Fund FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
CategoryXMonth FE	No	No	Yes	No	No	Yes	No	No	Yes
Month FE	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No

Table A3: Robustness test for R&A Ratings and fund flows - Only PRI funds
This table shows regressions of flows on an indicator variable for several cutoffs of the average Reporting & Assessment (∅R&A) scores of PRI signatories. These are respectively an average score of A or greater; greater then B but less then A; and one smaller then B. All regressions control for lagged fund characteristics and fund-family fixed effects. The odd columns also include moth fixed effects. The even ones control for category-by-month fixed effects instead. The sample includes only PRI signatories and spans from 2014 to 2019. Singleton observations are dropped. t-statistics, based on robust standard errors clustered at the fund-family and month level, are reported in parentheses. ***, **, and * indicate that the parameter estimate is significantly different from zero at the 1%, 5%, and 10% level, respectively. All variables are defined as in Appendix Table A1.

	All funds		Institutional		Retail	
	(1) Flows	(2) Flows	(3) Flows	(4) Flows	(5) Flows	(6) Flows
$\varnothing$R&A$_{t-1} \geq A$	0.03	0.00	0.23**	0.25**	0.01	0.01
	(0.60)	(0.10)	(2.10)	(2.56)	(0.20)	(0.27)
$\varnothing$R&A$_{t-1} \in [B; A)$	-0.04	-0.08**	-0.01	0.01	-0.02	-0.05
	(-1.00)	(-2.08)	(-0.14)	(0.08)	(-0.53)	(-1.29)
Observations	728,961	728,961	206,098	206,098	752,840	752,840
R-squared	0.02	0.05	0.04	0.07	0.03	0.05
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fund-Family FE	Yes	No	Yes	No	Yes	No
Category-Month FE	No	Yes	No	Yes	No	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes

Table A4: Robustness test for R&A Ratings and fund flows - Subset of R&A modules

This table shows regressions of flows on an indicator variable for several cutoffs of the average Reporting & Assessment ($\varnothing$R&A$^{restr.}$) scores of PRI signatories, using only a subset of modules (Strategy & Governance, Listed Equity Screening, Listed Equity Integration, and Active Ownership). These are respectively an average score of A or greater; greater then B but less then A; and one smaller then B. These indicators are set to zero for months when no ratings are available or the fund is not a PRI signatory. All regressions control for lagged fund characteristics and fund-family fixed effects. The odd columns also include moth fixed effects. The even ones control for category-by-month fixed effects instead. The sample includes all funds from countries with a least one PRI signatory and spans from 2011 to 2019. Singleton observations are dropped. t-statistics, based on robust standard errors clustered at the fund-family and month level, are reported in parentheses. ***, **, and * indicate that the parameter estimate is significantly different from zero at the 1%, 5%, and 10% level, respectively. All variables are defined as in Appendix Table A1.

	All funds		Institutional		Retail	
	(1) Flows	(2) Flows	(3) Flows	(4) Flows	(5) Flows	(6) Flows
$\varnothing$R&A$^{restr.}_{t-1} \geq A$	0.06	0.05	0.24**	0.21**	0.02	-0.00
	(1.28)	(0.93)	(2.48)	(2.32)	(0.32)	(-0.06)
$\varnothing$R&A$^{restr.}_{t-1} \in [B; A)$	0.02	-0.02	-0.05	-0.05	0.03	-0.01
	(0.34)	(-0.40)	(-0.54)	(-0.56)	(0.59)	(-0.26)
$\varnothing$R&A$^{restr.}_{t-1} < B$	-0.03	-0.06	-0.01	-0.05	-0.03	-0.07
	(-0.48)	(-1.03)	(-0.08)	(-0.31)	(-0.54)	(-1.18)
Observations	1,865,535	1,865,535	367,838	367,838	1,497,229	1,497,229
R-squared	0.03	0.05	0.04	0.06	0.03	0.05
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fund-Family FE	Yes	Yes	Yes	Yes	Yes	Yes
Category-Month FE	No	Yes	No	Yes	No	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes

Table A5: Robustness test for R&A Ratings and fund flows - Fund FEs

This table shows regressions of flows on an indicator variable for several cutoffs of the average Reporting & Assessment (∅R&A) scores of PRI signatories. These are respectively an average score of A or greater; greater then B but less then A; and one smaller then B. These indicators are set to zero for months when no ratings are available or the fund is not a PRI signatory. All regressions control for lagged fund characteristics, and fund fixed effects. The odd columns also include moth fixed effects. The even ones control for category-by-month fixed effects instead. The sample includes all funds from countries with a least one PRI signatory and spans from 2011 to 2019. Singleton observations are dropped. t-statistics, based on robust standard errors clustered at the fund-family and month level, are reported in parentheses. ***, **, and * indicate that the parameter estimate is significantly different from zero at the 1%, 5%, and 10% level, respectively. All variables are defined as in Appendix Table A1.

	All funds		Institutional		Retail	
	(1) Flows	(2) Flows	(3) Flows	(4) Flows	(5) Flows	(6) Flows
∅R&A$_{t-1} \geq A$	0.10**	0.09**	0.29***	0.25***	0.06	0.05
	(2.45)	(2.18)	(3.83)	(3.36)	(1.39)	(1.21)
∅R&A$_{t-1} \in [B; A)$	0.01	-0.02	0.07	0.06	0.01	-0.03
	(0.41)	(-0.60)	(0.93)	(0.77)	(0.17)	(-0.85)
∅R&A$_{t-1} < B$	0.03	0.02	0.08	0.07	0.02	0.01
	(0.69)	(0.47)	(1.01)	(0.98)	(0.42)	(0.22)
Observations	1,865,112	1,865,112	367,696	367,696	1,496,802	1,496,802
R-squared	0.10	0.11	0.11	0.13	0.11	0.12
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes
Category-Month FE	No	Yes	No	Yes	No	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes

Table A6: Robustness test for R&A Ratings and fund flows - Controlling for performance "Stars"

This table shows regressions of flows on an indicator variable for several cutoffs of the average Reporting & Assessment (∅R&A) scores of PRI signatories. These are respectively an average score of A or greater; greater then B but less then A; and one smaller then B. These indicators are set to zero for months when no ratings are available or the fund is not a PRI signatory. All regressions control for lagged fund characteristics – including performance "Stars" – and fund-family fixed effects. The odd columns also include moth fixed effects. The even ones control for category-by-month fixed effects instead. The sample includes all funds from countries with a least one PRI signatory and spans from 2011 to 2019. Singleton observations are dropped. t-statistics, based on robust standard errors clustered at the fund-family and month level, are reported in parentheses. ***, **, and * indicate that the parameter estimate is significantly different from zero at the 1%, 5%, and 10% level, respectively. All variables are defined as in Appendix Table A1.

	All funds		Institutional		Retail	
	(1) Flows	(2) Flows	(3) Flows	(4) Flows	(5) Flows	(6) Flows
$\varnothing$R&A$_{t-1} \geq A$	0.05	0.04	0.22**	0.20**	0.03	0.03
	(0.89)	(0.75)	(2.51)	(2.41)	(0.52)	(0.42)
$\varnothing$R&A$_{t-1} \in [B; A)$	-0.01	-0.04	0.01	0.00	-0.01	-0.05
	(-0.15)	(-0.97)	(0.18)	(0.04)	(-0.28)	(-1.10)
$\varnothing$R&A$_{t-1} < B$	-0.00	-0.02	0.02	0.03	0.01	0.00
	(-0.10)	(-0.34)	(0.16)	(0.27)	(0.16)	(0.01)
Stars$_{t-1}$	0.41***	0.40***	0.57***	0.55***	0.46***	0.46***
	(25.76)	(25.29)	(14.72)	(14.89)	(23.65)	(24.01)
Observations	1,883,481	1,883,481	371,101	371,101	1,511,500	1,511,500
R-squared	0.04	0.05	0.05	0.07	0.11	0.12
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fund-Family FE	Yes	Yes	Yes	Yes	Yes	Yes
Category-Month FE	No	Yes	No	Yes	No	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes

Table A7: Robustness test for R&A Ratings - Identification Test
This table shows regressions of flows on an indicator variable for several cutoffs of the average Reporting & Assessment (∅R&A) scores of PRI signatories. These are respectively an average score of A or greater; greater then B but less then A; and one smaller then B. The sample covers only signatories that either join before 2013, when submitting an R&A report became mandatory, or funds that do *not* file such report. These indicators are set to zero for months when no ratings are available or the fund is not a PRI signatory. All regressions control for lagged fund characteristics. Panel A drops also funds that are not PRI members. Panel B computes the cutoffs of the R&A framework using the restricted sample of modules. Panel C adds fund fixed effects instead of fund-family fixed effects. Panel D controls for the performance "Stars". The odd columns also include moth fixed effects. The even ones control for category-by-month fixed effects instead. The sample includes all funds from countries with a least one PRI signatory and spans from 2011 to 2019. Singleton observations are dropped. t-statistics, based on robust standard errors clustered at the fund-family and month level, are reported in parentheses. ***, **, and * indicate that the parameter estimate is significantly different from zero at the 1%, 5%, and 10% level, respectively. All variables are defined as in Appendix Table A1.

Panel A: Only PRI funds

	All funds		Institutional		Retail	
	(1) Flows	(2) Flows	(3) Flows	(4) Flows	(5) Flows	(6) Flows
∅R&A$_{t-1} \geq A$	0.06	0.03	0.28*	0.35**	0.05	0.06
	(0.93)	(0.47)	(1.97)	(2.58)	(0.80)	(1.02)
∅R&A$_{t-1} \in [B; A)$	-0.04	-0.08*	0.01	0.08	-0.01	-0.04
	(-0.73)	(-1.68)	(0.05)	(0.64)	(-0.26)	(-0.78)
Observations	541,291	541,291	159,455	159,455	581,715	581,715
R-squared	0.02	0.04	0.04	0.07	0.03	0.05
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fund-Family FE	Yes	No	Yes	No	Yes	No
Category-Month FE	No	Yes	No	Yes	No	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes

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Panel B: Subset of R&A modules

	All funds		Institutional		Retail	
	(1) Flows	(2) Flows	(3) Flows	(4) Flows	(5) Flows	(6) Flows
$\varnothing$R&A$^{restr.}_{t-1} \geq A$	0.03	-0.02	0.39***	0.32***	0.10	0.07
	(0.31)	(-0.17)	(3.37)	(2.85)	(1.50)	(1.15)
$\varnothing$R&A$^{restr.}_{t-1} \in [B; A)$	-0.06	-0.12	0.09	0.05	0.09	0.03
	(-0.57)	(-1.20)	(0.73)	(0.46)	(1.39)	(0.48)
$\varnothing$R&A$^{restr.}_{t-1} < B$	-0.16	-0.17	0.12	-0.01	-0.04	-0.06
	(-1.42)	(-1.54)	(0.46)	(-0.04)	(-0.49)	(-0.84)
Observations	706,880	706,880	283,977	283,977	1,189,269	1,189,269
R-squared	0.02	0.04	0.04	0.07	0.03	0.05
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fund-Family FE	Yes	No	Yes	No	Yes	No
Category-Month FE	No	Yes	No	Yes	No	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes

Panel C: Fund FEs

	All funds		Institutional		Retail	
Dep. variable:	(1) Flows	(2) Flows	(3) Flows	(4) Flows	(5) Flows	(6) Flows
$\varnothing$R&A$_{t-1} \geq A$	0.21***	0.19***	0.53***	0.45***	0.17**	0.15**
	(3.26)	(3.11)	(4.08)	(3.77)	(2.46)	(2.33)
$\varnothing$R&A$_{t-1} \in [B; A)$	0.11*	0.05	0.30**	0.25**	0.08	0.03
	(1.74)	(0.95)	(2.44)	(2.21)	(1.27)	(0.48)
$\varnothing$R&A$_{t-1} < B$	0.13*	0.10	0.32*	0.28	0.10	0.08
	(1.73)	(1.51)	(1.73)	(1.62)	(1.43)	(1.19)
Observations	1,473,279	1,473,279	283,864	283,864	1,188,916	1,188,916
R-squared	0.10	0.11	0.10	0.13	0.10	0.12
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes
CategoryXMonth FE	No	Yes	No	Yes	No	Yes
Month FE	Yes	No	Yes	No	Yes	No

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Panel D: Controlling for performance "Stars"

	All funds		Institutional		Retail	
	(1) Flows	(2) Flows	(3) Flows	(4) Flows	(5) Flows	(6) Flows
$\varnothing \text{R\&A}_{t-1} \geq A$	0.15**	0.13**	0.36***	0.30***	0.14**	0.13*
	(2.41)	(2.15)	(3.40)	(2.85)	(2.09)	(1.96)
$\varnothing \text{R\&A}_{t-1} \in [B; A)$	0.05	-0.01	0.14	0.09	0.06	0.01
	(0.78)	(-0.11)	(1.30)	(0.84)	(0.90)	(0.11)
$\varnothing \text{R\&A}_{t-1} < B$	0.06	0.03	0.11	0.08	0.08	0.06
	(0.83)	(0.46)	(0.68)	(0.50)	(1.12)	(0.92)
Stars_{t-1}	0.40***	0.38***	0.57***	0.54***	0.45***	0.44***
	(23.92)	(23.64)	(14.11)	(14.08)	(22.18)	(22.35)
Observations	1,488,055	1,488,055	286,543	286,543	1,200,797	1,200,797
R-squared	0.04	0.05	0.04	0.07	0.11	0.12
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fund-Family FE	Yes	Yes	Yes	Yes	Yes	Yes
Category-Month FE	No	Yes	No	Yes	No	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes

Table A8: Robustness test for R&A and ESG "Globes" ratings are complements This table shows regressions of flows on an indicator variable for funds with a high average R&A score of A or greater and its interactions with indicators for the number of Morningstar ESG Globes. The ∅R&A and Globes indicators are set to zero for months when no ratings are available or the fund is not a PRI signatory. The reference category is missing (0) Globes. All regressions control for lagged fund characteristics, and fund-family fixed effects. The odd columns also include moth fixed effects. The even ones control for category-by-month fixed effects instead. The sample includes all funds from countries with a least one PRI signatory and spans from 2011 to 2019. Singleton observations are dropped. t-statistics, based on robust standard errors clustered at the fund-family and month level, are reported in parentheses. ***, **, and * indicate that the parameter estimate is significantly different from zero at the 1%, 5%, and 10% level, respectively. All variables are defined as in Appendix Table A1.

	All funds		Institutional		Retail	
	(1)	(2)	(3)	(4)	(5)	(6)
Dep. variable:	Flows	Flows	Flows	Flows	Flows	Flows
∅R&A$_{t-1} \geq A$ × 5 Globes	0.16*	0.21**	0.41**	0.42**	0.11	0.17
	(1.68)	(2.21)	(2.33)	(2.31)	(1.05)	(1.63)
∅R&A$_{t-1} \geq A$ × 4 Globes	0.01	0.04	0.18	0.22*	-0.04	-0.01
	(0.19)	(0.60)	(1.40)	(1.73)	(-0.55)	(-0.22)
∅R&A$_{t-1} \geq A$ × 3 Globes	-0.04	-0.01	-0.01	0.02	-0.05	-0.02
	(-0.64)	(-0.19)	(-0.09)	(0.18)	(-0.78)	(-0.34)
∅R&A$_{t-1} \geq A$ × 2 Globes	-0.17***	-0.12**	-0.09	-0.01	-0.18***	-0.15**
	(-2.64)	(-2.02)	(-0.70)	(-0.09)	(-2.63)	(-2.21)
∅R&A$_{t-1} \geq A$ × 1 Globe	-0.09	-0.08	-0.04	0.01	-0.08	-0.09
	(-0.86)	(-0.78)	(-0.22)	(0.04)	(-0.75)	(-0.77)
5 Globes	-0.09	-0.04	-0.13	0.03	-0.08	-0.08
	(-1.39)	(-0.80)	(-1.04)	(0.20)	(-1.29)	(-1.41)
4 Globes	-0.12**	-0.06	-0.30***	-0.10	-0.07	-0.05
	(-2.16)	(-1.37)	(-3.58)	(-1.17)	(-1.21)	(-1.17)
3 Globes	-0.18***	-0.12***	-0.36***	-0.15*	-0.13***	-0.12***
	(-4.08)	(-3.53)	(-5.35)	(-1.93)	(-2.67)	(-3.25)
2 Globes	-0.15***	-0.10***	-0.32***	-0.12	-0.10*	-0.10**
	(-2.93)	(-2.63)	(-3.86)	(-1.34)	(-1.79)	(-2.41)
1 Globe	-0.25***	-0.18***	-0.39***	-0.18	-0.19***	-0.17***
	(-3.87)	(-3.03)	(-3.08)	(-1.43)	(-2.97)	(-2.83)
∅R&A$_{t-1} \geq A$	0.10*	0.07	0.22**	0.17*	0.06	0.03
	(1.70)	(1.23)	(2.40)	(1.89)	(0.97)	(0.56)
∅R&A$_{t-1} \in [B; A)$	0.01	-0.02	0.04	0.02	0.00	-0.04
	(0.32)	(-0.53)	(0.51)	(0.20)	(0.04)	(-0.82)
∅R&A$_{t-1} < B$	0.01	-0.01	0.04	0.05	-0.00	-0.02
	(0.15)	(-0.11)	(0.37)	(0.39)	(-0.09)	(-0.35)
Constant	0.53***	0.23	1.26***	0.77**	0.44**	0.17
	(3.15)	(1.37)	(3.82)	(2.42)	(2.42)	(0.96)
Observations	1,865,535	1,865,535	367,838	367,838	1,497,229	1,497,229
R-squared	0.03	0.05	0.04	0.06	0.03	0.05
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fund-Family FE	Yes	Yes	Yes	Yes	Yes	Yes
Category-Month FE	No	Yes	No	Yes	No	Yes
Month FE	Yes	No	Yes	No	Yes	No

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