Investment fund similarity, climate exposures and the risk of financial contagion

Ulf Lewrick[a,b,*], Abhishek Srivastav[c], and José M. Vidal Pastor[b]

April 2025

Abstract

We investigate the financial stability risks posed by climate change, focusing on the role of equity investment funds in amplifying climate shocks through fire-sale spillovers. Using a novel measure of portfolio similarity based on exposure to "brown assets", we show that funds with higher climate risk exposures experience greater outflows, prompting disproportionate sales of brown assets. These sales trigger spillovers to peer funds holding similar portfolios, amplifying systemic risks. The findings highlight the feedback loop between fund flows, asset prices, and real economy impacts, underscoring the need for enhanced risk management and regulatory frameworks to address climate-related financial risks.

JEL classification: G01; G11 ; G23; D62.

Keywords: Climate risk; carbon emission; non-bank financial intermediation; financial stability.

Disclaimer: The views expressed in this article are those of the authors and do not necessarily reflect those of the Bank for International Settlements or of the Financial Stability Board. All errors are our own.

Declarations of interest: none.

[a] Bank for International Settlements, Centralbahnplatz 2, CH 4002 Basel, Switzerland.
[b] University of Basel, Peter Merian-Weg 6, 4052 Basel, Switzerland.
[c] Financial Stability Board, Centralbahnplatz 2, CH 4002 Basel, Switzerland.
* Corresponding author. Email: ulf.lewrick@bis.org.

1 Introduction

Financial risks from climate change are a key priority for financial authorities across various jurisdictions. Transition risks, stemming from the shift to a low- or net-zero-emissions economy, and physical risks, arising from the failure to achieve this transition, can have profound adverse effects on the real economy. These risks can affect financial institutions through the established transmission channels (e.g. market risk, credit risk, liquidity risk) and need to be embedded in the risk management strategy. Poorly managed risks could create correlated shocks whose impact can be magnified as they propagate through the financial system, in a similar manner to other types of financial shocks (Financial Stability Board, 2025).

There is, however, a surprising disconnect between empirical research by academics and what financial authorities observe in practice. Academic research shows that climate risks have implications for asset pricing (Bolton and Kacperczyk, 2021, 2023) and that investors should embed climate risks in their risk management frameworks (Krueger et al., 2020; Pastor et al., 2021). However, forward-looking analytical approaches, such as climate scenario analyses, used by various financial authorities show subdued direct financial impacts of climate shocks on the financial system (FSB-NGFS, 2022; European Supervisory Authorities and ECB, 2024; Federal Reserve Board, 2024).

One reason these findings diverge from priors about the salience of climate risks is the limited evidence on how the financial system itself can amplify such shocks. This amplification can stem from structural features of the financial system, such as direct and indirect interconnections across sectors or jurisdictions, which can accumulate imbalances and intensify stress. Recent events, including the US banking turmoil in March 2023, forced sales by UK liability-driven investment funds in 2022, and large-scale redemptions of money market funds during Covid-19, demonstrate that second-round effects can be substantial. Overlooking how financial institutions, both individually and systemically, might amplify climate shocks risks fostering undue complacency. This could lead to inefficient resource allocation, hinder global policy efforts to mitigate climate change, and heighten the risk of financial instability.

Our paper provides empirical evidence on how climate-related financial risks can give rise to systemic risks through the interconnectedness of investment funds, who are key investors

in global equity markets. Existing research largely focusses on individual asset pricing and direct exposures but overlooks the role of interconnectedness among financial institutions in propagating climate risks. This paper addresses this gap by introducing a novel measure of portfolio similarity, which captures how funds' exposure to "brown assets" – industries with high greenhouse gas (GHG) emissions – can lead to fire-sale spillovers. By applying this measure to equity investment funds, we provide new insights into how climate shocks propagate through financial markets, amplifying systemic risks (Chen et al., 2010; Falato et al., 2021; Girardi et al., 2021).

We show that climate shocks can trigger investor redemptions in equity funds, particularly those with high exposure to brown assets. Anticipating further withdrawals, fund managers may sell assets beyond immediate redemption needs (e.g. Morris et al, 2017). These sales depress asset prices (e.g. Ma et al., 2022), hurting the performance of peer funds holding similar portfolios and prompting further investor redemptions (Coval and Stafford, 2007; Chen et al., 2010; Falato et al., 2021; Girardi et al., 2021). This adverse feedback loop, driven by strategic complementarities among not only fund investors but also fund managers creates a feedback loop that amplifies systemic risks. Our analysis focuses on how portfolio similarity among funds exacerbates these dynamics in response to climate-related shocks.

To assess the systemic risks arising from climate shocks, we develop a novel measure of portfolio similarity. Unlike existing approaches that focus on common holdings of identical assets, our measure captures vulnerabilities stemming from funds holding similar – but not identical – securities. Drawing on regulatory concerns about growing similarity in holdings (FSB, 2021; IMF, 2023), we calculate portfolio similarity between any two given funds using a cosine similarity metric (Girardi et al, 2021), focussing on exposures to brown industries. Industries are classified as "brown" if their Scope 1 and 2 GHG emissions intensity exceeds the 75th percentile during the sample period. This approach allows us to identify clusters of funds with high "brown similarity" that are particularly vulnerable to correlated shocks, providing a new perspective on climate-related financial stability risks.

Our measure of similarity is designed to reveal vulnerabilities due to network linkages among funds that give rise to common exposures to climate shocks. Figure 1 illustrates how the concept of brown similarity can change the perspective on potential pressure points. While major equity funds exhibit modest similarity at the full portfolio level, i.e. they are "spread out"

(Panel A), a cluster of tightly interlinked funds with high exposure to brown assets emerges from the analysis of their brown similarity (Panel B).

[Figure 1 about here]

Formal regression analysis shows that funds with higher climate exposures are more vulnerable to outflows, with investors responding to these exposures even after accounting for fund performance.[1] In turn, these funds disproportionately sell brown assets, amplifying downward price pressure through correlated trading. We show that higher portfolio similarity among funds leads to greater commonality in asset sales, with a one standard deviation increase in brown similarity resulting in a 73% rise in aggregate changes to brown portfolios.

Flow pressure from peers with similar climate exposures amplifies the adverse effects on fund flows and performance. Following the literature (e.g. Chernenko and Sunderam, 2020, Coval and Stafford, 2007), we construct a measure of flow pressure as the weighted average of flows in peer funds, where the weights reflect the pairwise similarity of their brown holdings. This approach captures the incremental impact of spillovers, demonstrating how peer-driven outflows exacerbate the effects of an initial adverse shock. Our analysis reveals a strong positive relationship between flow-driven peer pressure and fund outflows, highlighting the role of brown similarity in amplifying spillovers. Specifically, a one standard deviation increase in flow-driven peer pressure reduces fund flows by an average of 19 basis points of total net assets (TNA) and by as much as 82 basis points for funds in the 5th percentile, as shown in quantile regressions.

These spillovers extend to the real economy, as increased volatility and valuation losses in brown assets raise the cost of capital for affected firms. Specifically, a one standard deviation increase in flow pressure raises volatility by 1.8 basis points, which represents one-third of the impact of a one standard deviation decrease in equity returns on volatility (6.5 basis points) in our sample. Additionally, we observe that peer outflows driven by brown similarity lead to lower equity returns for brown assets, while no such effect is found for other assets. These

[1] If climate risk were already fully priced in fund returns, brown exposure should have no additional explanatory power in addition to returns. Our finding that investors do respond to brown exposure implies that they may have heterogenous expectations on the salience of these risks, e.g. in terms of materiality, proximity, or the channels through which they may materialise.

results highlight the broader economic consequences of climate-related financial spillovers (e.g. Bolton and Kacperczyk, 2021, 2023; Sautner et al., 2023).

Our paper makes two key contributions. First, we add to the growing literature on financial risks from climate change for individual firms (Zhang, 2024; Bolton and Kacperczyk, 2023; Hsu et al., 2023). While there is evidence that climate risks are increasingly being priced into asset valuations, significant uncertainty remains regarding the magnitude and timing of these risks. This uncertainty fuels disagreements among investors about the salience of climate risks (Chen et al., 2012; Goetzmann et al., 2016; Gao et al., 2018; Giglio et al., 2024). From a macroeconomic perspective, our paper highlights how spillovers lead to additional fund outflows based on the similarity of funds' holdings to others in the system, beyond the direct impact of returns. This dynamic creates a feedback loop in which the initial negative pricing impact of climate risks is amplified by herding behaviour, exacerbating systemic vulnerabilities.

Second, we extend the evidence in the growing literature on strategic complementarities among investors (Chen et al., 2010; Chernenko and Sunderam, 2020; Falato et al., 2021). Previous studies have shown how interconnectedness, driven by commonality in asset holdings, can amplify financial shocks, both in banks (Khametshin and Srinivasan, 2024; Goldstein et al., 2024) and in non-bank financial intermediaries (Girardi et al., 2021; Georg et al., 2024). For instance, Georg et al. (2024) demonstrate that U.S. money market funds divest from securities when they hold more assets in common with other holders of the same security, as investors internalise the risk of future liquidation costs. Our paper builds on this literature by focusing specifically on exposure to climate risks, which provides a natural setting due to the heterogeneity in investor beliefs about the salience and timing of these risks. Greater uncertainty about climate risks increases the likelihood of abrupt reactions to adverse shocks. In this context, we show that the impact of flow-driven peer pressure on fund flows is significantly stronger for funds with higher climate exposures. Importantly, we demonstrate that climate risks can simultaneously affect multiple industries, and our analysis departs from prior work by showing that funds may be impacted even when they hold similar—but not identical—assets.

Our findings are also highly relevant to ongoing debates among academics, practitioners, and regulators regarding the sources of systemic risk from climate-related financial risks (Financial Stability Board, 2022). Our results suggest that equity funds may not fully internalise

the broader impact of climate shocks on their trading behaviour. This creates stronger incentives for discretionary sales, which, in turn, generate spillovers to other funds. These findings underscore the need for enhanced regulatory frameworks and systemic risk monitoring tools to address the vulnerabilities posed by climate-related financial risks.

The remainder of this paper is organised into three sections. Section 2 provides an overview of the datasets and methodology, including the construction of the novel measure of portfolio similarity based on climate exposures. In Section 3, we present the empirical results, focusing on the dynamics of fund flows, spillovers, the amplification of systemic risks through portfolio similarity, and the feedback effects of these spillovers on the real economy through their impact on equity volatility and funding costs. We conclude in Section 4 with a discussion of policy implications and avenues for future research.

2 Data and methodology

2.1 Selection of funds and holdings

Our analysis combines granular data from three main sources.

We select from Lipper (LSEG Data & Analytics) the quarterly portfolio holdings at the ISIN-level (i.e. equity issuer level) from March 2015 to December 2021 of all reporting US equity funds.

We match the holdings data with information from Lipper on fund flows and fund performance, which is available at the share class level. We follow the standard approach in the literature and aggregate the share-class information at the fund-level using value-weighted averages in order to align the data with the holdings data.

Next, we combine the Lipper data with information on the equity issuers based on matching the ISINs with firm-level financial data from S&P Global Market Intelligence. For each equity issuer, we collect information on sector, location, equity pricing and financial performance indicators, financial statements, and environmental disclosure indicators.

Finally, we merge the dataset with annual information on each equity issuer's Scope 1 and 2 GHG emissions obtained from S&P Trucost. This information is used to calculate the funds' climate risk exposure as discussed in the next section.

Overall, our sample comprises 3,575 US equity funds for which holdings data and information on the GHG emissions of their investments were available. Table 1 presents summary statistics of the fund-level variables (Panel A) and of the stock-level variables (Panel C), respectively, with additional detail on the variable definitions provide in Annex Table A1.

[Insert Table 1 about here]

2.2 Measuring funds' climate exposure

We construct a proxy for *climate exposure at the industry level* based on the equity issuers' emissions intensity. We define the latter as the Scope 1 and 2 GHG emissions, normalised by the firm's revenues in the corresponding period. To categorise industries as *brown*, *green* or *neutral*, we calculate the 25th and 75th percentiles of the sample distribution in each year and identify brown industries as those that have emission intensities over the 75th percentile (Figure 2, Panel A), and green industries as those that have emissions intensities below the 25th percentile (Figure 2, Panel B), respectively. To avoid frequent recategorisations of industries, we consider industries to be brown/green only if they are consistently ranked in the top/bottom-quartile for the full sample period.

[Insert Figure 2 about here]

As a next step, we calculate the *brown and green shares* of the fund portfolios based on the total market value invested in brown and green industries as a percentage share of the portfolio's total market value in each period.

We then compute the *funds' climate exposure* as the weighted average of the climate exposure of each industry's exposure to climate risks. We use the firm-level climate change exposure developed in Sautner et al (2023) that captures climate discussions in earnings call transcripts across three dimensions: risks from climate policies (transition risks), direct impacts from extreme weather events (physical risks), and mentions of business opportunities from climate change. This variable serves as a forward-looking measure of how firms perceive and disclose their exposure to climate change. We transform Sautner et al.'s (2023) firm-level measure to one that represents exposures at the industry-level by calculating the weighted mean of climate exposures of each firm in a given industry, where weights correspond to firm

size. Fund-level climate exposures then follow by multiplying each industry's climate exposure and the fraction of the fund portfolio allocated to that industry.[2]

There is considerable variation in exposure to climate risks over time and, even more noticeably, in the cross-section of funds (Figure 3). Several funds exhibited exceptionally large exposures over the period of observation (dots at the top-end of Figure XY2), illustrating how the fund-level measure offers a more nuanced picture of climate exposures than a mere aggregation of funds' holdings of brown assets.

[Insert Figure 3 about here]

2.3 Measuring "brown similarity"

Clusters of funds that are similar in terms of their climate exposures, which could then collectively be exposed to abrupt climate shocks, could represent a source of systemic risk. In this context, funds that are more similar would be more likely to sell similar brown assets and exacerbate systemic risk concerns. We quantify this notion of funds' "brown similarity" by measuring network linkages among funds due to common exposure to climate risks. Based on the concept of cosine similarity proposed by Girardi et al. (2021) for insurers' portfolios, we calculate brown similarity for each pair of funds i and j as:

$$Brown\ similarity_{ijt} = \frac{w_{it} * w_{jt}}{||w_{it}|| * ||w_{jt}||} \quad (1)$$

This measure represents the cosine similarity between the brown shares of the portfolios of a given pair of funds in period t as the dot product of the pair's portfolio weight vectors of their brown assets, *w*, normalized by the vectors' lengths.

We compute portfolio weights at the brown industry-level for the main results of this paper but show that results remain similar if we instead use a more granular measure that computes similarity using ISIN-level portfolio weights.

Brown similarity is equal to one for two funds with the same exposure to brown industries ("perfect similarity"), whereas it is equal to zero if the funds invest in different brown industries

[2] We rely on industry-based measures to be consistent with how we measure similarity that is also computed at the industry-level. Results are very similar if we instead use weights based on the fraction of portfolio allocated to different firms (i.e., performing the analysis at the ISIN-level).

with no overlap. In principle, funds could also be "perfectly dissimilar" (brown similarity equal to minus one), if one fund shorts exactly those brown industries with the same amount in which the other fund

Figure 4 illustrates the additional interlinkages that brown similarity uncovers relative to focussing only on brown shares based on an example of three selected funds from the sample: Fund 1 has a brown share of 15%, notably more than Fund 2 (10%), and closer to the share of Fund 3 (12%). However, Fund 2 is nearly perfectly similar to Fund 1 and to Fund 3, with a brown similarity of close to 1 in both cases, whereas the brown shares of Fund 1 and Fund 3 are distinct, with a brown similarity of less than 0.1. The risk of concerted sales of similar brown assets is therefore pronounced for the former fund pairs, but notably more remote for the latter.

[Insert Figure 4 about here]

Several factors drive the similarity of funds' exposure to brown assets and the similarity of their portfolios more generally. To assess this formally, we regress our measure of similarity on the size-weighted average of key measures of fund performance at the fund-pair level following the approach for insurers in Girardi et al. (2021). We also include binary variables for large fund pairs and their regional focus (e.g. global funds). Our estimates (see Table A2 in the Annex) show that pairs of larger funds and of those that allocate funds to the same region are more similar to each other with regard to their entire portfolio.[3] Notably, a higher share of investments in brown industries is associated with less similarity at the overall portfolio level, indicative of funds with higher brown exposures diversifying their non-brown share by investing in multiple non-brown industries. By contrast, funds that are similar with regard to their brown investments, also tend to be more exposed to brown assets. This accords with the clustering of "brown funds" visualised in [Figure 1], pointing to the risk of concerted responses to climate shocks.

Adding to the summary statistics in [Panel B of Table 1], we provide additional statistics on brown similarity and measures of performance at the corresponding fund-pair level. While the median brown similarity amounted to about 0.36 during the period of observation, with

[3] For regressions based on portfolio similarity, we calculate similarity as in equation (1) but use the entire portfolio rather than only the allocation to brown industries.

XX% of fund-pairs being perfectly dissimilar in a given quarter, around 10% of fund-pair observations recorded brown similarity of at least 0.8.

3 Empirical analysis

The empirical analysis is structured in four steps that together provide a comprehensive view on how funds' exposures to climate risks may give rise to financial stability risks:

- **Enabling conditions**. First, we show that fund flows respond to changes in climate exposures and that fund managers react to these outflows by selling brown stocks.
- **Concerted trading.** Second, we provide evidence that fund pairs holding similar brown assets subsequently engage in concerted trades, suggesting that funds are not fully internalising their trading response to climate shocks.
- **Spillover effects.** Third, we illustrate that the negative externalities induced by outflows at other funds holding similar assets – flow-induced pressure – aggregates to affect a given fund's performance (returns and flows).
- **Feedback to real economy.** Finally, we show how these spillover effects affect the real economy by raising the volatility of stocks affected by flow-induced pressure.

3.1 Enabling conditions

We document that fund flows are sensitive to the fund's climate exposures on top of returns and while also controlling for other fund-level determinants. If climate risk were already fully priced in fund returns, brown exposure would have no additional explanatory power over returns. But, if investors respond to climate exposures either because they have heterogenous expectations on the salience of these risks –in terms of materiality, proximity, or the channels through which they may materialise– then we should find an economically meaningful impact.

To test for this, we use the following fund-level specification:

$$Y_{j,t+1} = \alpha + \beta \times Climate\ exposure_{j,t} + \gamma \times \boldsymbol{X}_{j,t} + \theta_j + \delta_t + \varepsilon_{j,t} \quad (2)$$

where the dependent variables are either the net flows or returns for fund *j* in quarter *t+1*. The main variable of interest is the fund's climate exposure (recall Section 2.2), calculated as the weighted average of each industry's exposure to climate risks with weights corresponding to the fraction of fund portfolio allocated to that industry. $X_{j,t}$ is a vector of controls at quarter *t* for fund characteristics used throughout the literature. These include fund flows, returns,

volatility, size, age, tracking error, and cash holdings (see also Table 1). To address unobserved heterogeneity, we control for fund fixed effects (θ_j) and time fixed effects (δ_t) in all specifications.

An increase in funds' climate exposure has been associated with (net) fund outflows during the sample period (Table 2, Panel A, column 1). Specifically, a one standard deviation increase in climate exposure has been associated with a 28 basis points increase in outflows, equivalent to about one third of the average outflows, or one third of the impact of a one standard deviation decline in (lagged) returns.[4] At the same time, the same increase in climate exposure has been associated with an improvement in fund returns by around 32 basis points, potentially indicating that investors demand higher premium for holding such stocks.

[Insert Table 2 about here]

Next, we test if this relationship is stronger for funds that are more similar to their peers with regard to their exposure to brown assets. To do so, we calculate the average brown similarity of a given fund relative to all other funds in the sample and interact it with a tercile-based measure of climate exposure.

The sensitivity of fund flows to climate exposures increases significantly for funds that are more similar (Panel B of Table 2). Specifically, it becomes nearly twice as large as we move from the bottom to the top tercile in terms of similarity in brown asset holdings. The interaction terms together are statistically significant (p-val = 0.002). Moreover, the difference in coefficients between low and high similarity pairs, and medium and high similarity pairs rejects the null at p-value < 0.001 (Panel D). By contrast, the difference in coefficients between low and medium similarity fund-pair is not statistically different from zero. Therefore, the expectation that other investors that hold similar assets will withdraw their money reduces the expected return from staying in the fund and increases the incentive for each individual investor to withdraw as well. For the impact on fund performance, we see that the marginal impacts are not economically significant – the sensitivity of fund returns to climate exposures is nearly the same for funds in the bottom and top percentile in terms of similarity in brown asset holdings.

[4] We calculate this by standardizing all coefficients, except the lagged outcome variable. A one standard deviation increase in returns results in increasing flows by 0.930 basis points as compared to 0.283 for one standard deviation increase in climate exposures. Sample mean for the outcome variable is -0.878

In response to fund flows, fund managers may adjust their portfolios in two ways: 1) allocate more/less cash or 2) trade some of fund's asset holdings. To empirically test which of these explanations prevail in our sample, we assess the impact of fund flows on changes in fund-level measures of cash allocations, changes in brown assets and non-brown assets. If exposures to climate risk is a salient concern in the cross-section, we should see funds with higher climate exposures sell more of their brown assets in response to outflows. On the other hand, under the climate agnostic view, we should observe more balanced set of results where funds sell a pro rata share of their portfolio spread across cash, brown and non-brown holdings, in response to outflows.

At the outset, we note that there is some degree of cross-sectional variation in funds' trading behaviour – such patterns are not clustered to just a few quarters or for a small set of industries (Figure 6). Over the sample period funds buy brown industries in more quarters as opposed to selling them, and there is significant sectoral variation when it comes to brown industries.

[Insert Figure 6 about here]

Moving to the multivariate tests, Table 3 shows that funds with higher climate exposures are more aggressive in adjusting the holdings of their brown assets when responding to fund outflows – both, in absolute terms (column (2)) and relative to the fund value (column (5)). Moving the climate exposure from its 25th percentile to 75th percentile, we would see $ 1.39 MM of *additional* sales for an average fund (AuM: $2,210 MM) in our sample, which is 70% increase relative to the average trade in brown industries. When looking at the relative amounts traded, the results remain equally meaningful. Using the results shown in column (5), we find that one standard deviation increase in climate exposure results in a nearly 50% higher sensitivity of funds to decrease in the brown part of the portfolio when responding to fund flows.[5]

[Insert Table 3 about here]

We run a battery of robustness checks to explore alternative explanations. In particular, we examine the possibility that our results are driven by fund's geographic focus (using time-

[5] The coefficient for interaction term Fund Flows X Climate Exposure is 0.107 in column (5), while the standalone coefficient for fund flows is 0.240. This means increasing climate exposure by 1 standard deviation increases the sensitivity of fund flows to changes in brown part of the portfolio by 0.107/0.240.

varying factors that could affect funds' investment strategy in different geographical regions), and [placeholder for more such tests]. Table 4 column (1) shows the results of a different robustness test Row 1 replicates our baseline results from Table 2. For compactness, we only report the coefficient on our variable of interest – fund's climate exposure. It is worth noting that some of the alternative explanations we examine do affect how funds manage their flows. That is, the controls we add to the regression do themselves enter significantly. However, controlling for these alternative explanations does not affect our key result that higher climate exposures are associated with higher(lower) fund outflows (inflows).

[Insert Table 4 about here]

Next, we examine the possibility that funds' climate exposure is simply a proxy for performance-flow relation. The fact that funds accommodate fund flows through trading their portfolio securities instead of cash could be driven by fund managers' expectations of future returns. For instance, if the manager expects future returns to be low, they may want to satisfy redemption requests by selling the overvalued brown stocks. To test if our climate exposure measure is correlated with expected returns, we add controls for future returns realized over the following four quarters (column (2) of Table 4). These controls do not affect the coefficient of interest.

3.2 Concerted trading

In the previous section, we find that funds with high climate risk exposures would experience a negative impact on fund flows and these funds are more likely to decrease allocations to brown industries in their portfolios. This could have significant implications for financial stability if investment funds react to large outflows in ways that amplify the initial shocks, such as shedding similar types of assets simultaneously. In other words, systemic risk will be higher if there are higher commonalities in asset sales (or buys) across similar funds, beyond that implied by standard fund-level determinants.

We test for this by calculating the degree of common sales between similar types of fund-pairs. Our study departs from prior work that looks at funds selling the same firms in their portfolios to one that accounts for the fact that climate risks can affect multiple sectors at once and therefore funds could also sell similarly exposed assets to amplify climate shocks. We

measure common sales between any two funds as the dot product of a pair's quarter-end net sales vectors at the industry-level, following Girardi et al. (2021). This can be expressed as:

$$Common\ Sales_{ijt} = \boldsymbol{NetSales}_{i,t}.\boldsymbol{NetSales}_{j,t} \quad (3)$$

where **Net Sales** is the vector showing changes in the market value of holdings for different industries where the fund has invested in quarter *t*.

Figure 7 presents the quarterly time-series average of *Ln* (1 + *Common Sales*) level for subsamples of large fund pairs and all other pairs excluding large investment funds. We do not see any obvious clustering of common sales over the sample, although there appear to be spikes in the size of portfolio changes. For instance, the Q4 2018 period was characterised by market-wide changes when repricing took place amid mixed signals from global economic activity and the gradual, yet persistent, tightening of financial conditions (BIS Quarterly Review, 2018). Similarly, the Q1 2020 period also shows elevated levels of common sales that correspond to the Covid-19 period.

[Insert Figure 7 about here]

For the multivariate tests, we run the regression at fund-pair level using the following specification:

$$Y_{i,j,t+1} = \alpha + \beta \times Brown\ similarity_{i,j,t} + \gamma \times \boldsymbol{X}_{i,j,t} + \theta_{i,j} + \delta_j + \rho_i + \mu_t + \varepsilon_{j,t} \quad (4)$$

where brown similarity is our key variable of interest, which reflects the cosine similarity of fund-pairs in the brown part of their portfolio, $\boldsymbol{X}_{i,j,t}$ is the vector of fund pair covariates which is the size-weighted average of the respective fund variable (fund size, performance, tracking error, and flows). The regression includes fund-pair and individual fund fixed effects to account for any unobserved time-invariant determinants across and within funds. We also include time fixed effects to account for time trends that may systematically affect both the outcome variable and fund similarity.

We hypothesise a positive association between similarity and common sales. This will provide us a with a firm foundation to develop a narrative consistent with fund interlinkages resulting in correlated sales. However, documenting this empirically is not straightforward. If climate risks are already priced in equity prices, managers may opt keep their brown holdings

and instead strategically select other assets to liquidate in order to avoid further downward pressure on prices (Chen et al., 2010; Chernenko and Sunderam, 2020).

Table 5 provides strong evidence that funds indeed sell more in common if they are similar in the brown part of their portfolios; one standard deviation (= 0.31) increase in brown similarity results in increasing the aggregate changes by 73% (37.5/51.6) relative to the sample mean shown in Panel B of Table 1 (51.6). Assuming both funds sell the same amount of brown assets in their portfolios, this corresponds to nearly $6 mm portfolio-level changes by these funds, which is 1.5 times the average change in market value of brown assets held by an average fund in our sample.[6]

[Insert Table 5 about here]

We note that the tight link between brown similarity and common sales of brown assets is not mechanical. Figure 8 provides an example of three fund pairs that have different levels of brown similarity and common brown sales. While Fund 1 and Fund 3 have low brown similarity (0.09), their common sales exceed those of Fund 1 and Fund 2 for which similarity is significantly higher (0.95) because Fund 3's sales are concentrated in three industries, including the one where Fund 1 sells its stocks, whereas Fund 2's sales are more dispersed.

[Insert Figure 8 about here]

As a next step, we assess if the impact of similarity is asymmetric – are similar funds more likely to engage in correlated sales rather than purchases? To do so, for the aggregate sales variable, we compute our outcome variable only when the fund engages in sales (i.e. there is a decrease in portfolio allocated to a particular industry) and treat all other observations as zero (i.e. if the fund engages in buys or there is no shift). We follow the same process when calculating aggregate buys.

While there is a positive association for both aggregate sales and buys, the magnitude for aggregate sales is much higher than for aggregate buys in our sample (Table 5, columns (2) and (3)). Using the same approach as before, we find that one standard deviation increase in brown similarity results in increasing aggregate sales by 157% (32.75/20.77), relative to the

[6] Calculation details: Assuming funds decide to change their portfolio allocations to brown industries by the same amount at fund-level = Sqrt (37.5) = 6.12 MM. Average (median) holding of brown assets (fund-level) = 218 MM (37 MM). Average (median) change in holding of brown assets (fund-level) = 4 MM (0.313 MM)

sample mean (20.77). This translates to nearly $5.7 mm sales of brown assets by these funds or 2.6% (15.4%) of the size of the brown portfolio of an average (median) fund in our sample.[7] For common buys, we find that the effect of one standard deviation increase in brown similarity results in increasing aggregate buys by 3.7% (1.65/44.4) or $1.28 mm in buys.

As a final step, we assess whether the sensitivity of common sales is higher when fund-pairs face more outflows simultaneously. We test this by interacting brown similarity with the weighted average of fund flows, as shown in columns (7)-(9). When the pair-level measure of flows moves from median to the 10th percentile (i.e., both funds start experiencing extreme outflows), the sensitivity of common sales to brown similarity increases by 38%.[8] In line with prior results, fund-pair outflows have a meaningful effect when looking at common sales but not when considering common buys.

3.3 Spillover effects

Our results on common sales provide an early indication that there are potential strategic complementarities where funds engage in a greater degree of correlated trading when they have similar exposures to brown assets. Such behaviour may also result in spillovers to other funds. Consider a fund *A*. When other funds that hold similar stocks as fund *A* suffer outflows, their sales of overlapping stocks may drive down prices and fund A's returns, beyond what is implied by any concurrent changes in the fund's flow-performance relationship. It is through this "downstream" price pressure channel that redemptions "upstream" at fund A and may spill over onto those of fund B.

In this section, we test the degree to which flows into one fund impact the performance of other funds holding similar securities. The basic idea behind our approach is that flow-driven pressure is transferred between funds that are similarly "exposed" to each other. For any given fund, spillover concerns are more acute if it is more "similar" to other funds in the sample and whether its peers (in aggregate) are also experiencing extreme flows. Our approach therefore pivots from fund-specific narrative to the system-level one where we are

---

[7] Calculation details: Assuming funds sell the same amount of brown assets at fund-level = Sqrt (32.75) = 5.72 MM. Average (median) holding of brown assets (fund-level) = 218 MM (37 MM). Therefore, the % of brown portfolio that was shed = 5.7/218 * 100. Average (median) change in holding of brown assets (fund-level) = 4 MM (0.313 MM). Therefore, the magnitude of increase in common sales relative to what we observe in the sample = 5.7/4 = 1.4 times.

[8] As shown in column (7) of Table 5, (-7.814 (median, shown in Table 1 Panel B) - -101.9 (10th percentile, shown in Table 1 Panel B)) X -0.141(interaction term coefficient, Table 5) } / 34.775 (coefficient of brown similarity, Table 5)

concerned about the aggregate effect of externalities when several different funds experience capital withdrawals, which leads them to sell underlying securities in a correlated manner.

We compute flow-driven peer pressure, which is the weighted average of flows in peer funds where weights correspond to the fund-pairwise similarity of their brown holdings, as shown in equation (1). This variable shows the incremental impact, i.e., spillovers lead to "additional" outflows over and above the initial effect of a given adverse shock.

$$Brown\ peer\ pressure\ j,q\ = \sum(Normalised\ flow\ p,q * Brown\ similarity\ j,p,q) / \sum(Brown\ similarity\ j,p,q) \quad (5)$$

where *Normalised Flow* is the flow of peer fund p in quarter q normalised by assets under management of fund p. Since our focus is on pressure due to potential fire sales, we follow prior literature (Coval and Stafford, 2007; Falato et al., 2021) in focusing on funds where large fractions of volume are accounted for by mutual funds experiencing significant outflows. Consequently, we only include flows of the peer funds that are under the 10th or over the 90th percentile of the corresponding quarter. In this way, we capture the flow-driven pressure which is induced by the extreme flows of peer fund.[9] *Brown sim* is the pair-wise similarity of the brown holdings measured using industry classification of fund j with fund p in quarter q. For ease of interpretation, we multiply our measure by minus 1, so that higher values of flow-driven peer pressure imply more outflows.

Table 6 provides supports the notion of climate exposure-related spillovers: a positive coefficient on peer flow pressure implies that funds face higher outflows when their peers – funds with holdings similar with regard to the brown share of their portfolio – also face outflows. There is a spillover effect due to brown-similarity. This relationship holds after including fund and time fixed effects, fund covariates, including past lagged performance and various other covariates. One standard deviation increase in flow-driven peer pressure results in decreasing fund flows by 19 basis points (sample mean = -0.878).

[Insert Table 6 here]

We also run quantile regressions to explore if the relationship is stronger when flows are extreme in columns (4)-(6). The flow-driven peer pressure – fund flow sensitivity is stronger

[9] Our results remain robust to an alternative measure of fund flow pressure that uses the sample of all peer funds and weighs them by their respective fund flows. The results are shown in Table A3 of the annex.

when focusing on the tails with one standard deviation increase in flow pressure resulting in 57 basis points at the 10th percentile and 82 basis points at 5th percentile when running quantile regressions. In terms of relative importance, the marginal effect of flow pressure is similar to that of cash holdings and a third of the impact of performance on fund flows. In unreported tests, we confirm that the results remain similar if we also include flows across all peer funds and not just when the funds face extreme flows.

We also show similar findings when looking at the impact on fund returns (columns (7)-(8) of Table 6). The positive coefficient on flow-driven peer pressure implies that when funds that have holdings that are similar to fund A (in brown part of the portfolio) have outflows, fund A also has lower returns. The spillover effect on fund returns is also economically significant and strongly asymmetric for extreme negative returns, with a 1-SD increase in flow-driven peer pressure leading to an almost 15.9 basis point decrease in fund returns (sample mean = 3.38%). Moreover, column (8) shows that a one standard deviation increase in flow pressure induced by peers also results in a 1% higher likelihood of extremely negative fund returns, which are defined as fund returns that are below the 10th percentile in a given quarter. When comparing this with the unconditional mean for likelihood of extreme negative returns (10.6%), the impact of flow pressure is still economically significant. Taken together, these results indicate that fire-sale spillovers have material valuation consequences in the equity market.

3.4 Feedback to real economy

If fire-sale spillovers lead to redemptions, an intriguing possibility is that redemptions may lead in turn to further sales and thus to a spillover effect on prices or a "second-round" price impact (Falato et al., 2021). Greenwood and Thesmar (2011) show that stocks held by funds with volatile or highly correlated fund flows experience higher volatility. As these funds trade the same stocks at the same time in response to inflows and outflows, their trading activity introduces excess volatility in the returns of the underlying stocks.

We test for this using the specification shown below (equation (6)). Specifically, we test whether peers' flow-induced pressure generates feedback that are strong enough to further depress asset values. Since we define peers based on how similar they are in their holdings of

brown assets, we expect feedback effects for brown firms but not for firms categorised as green.

$$Y_{i,t+1} = \alpha + \beta \times \boldsymbol{Brown\ peer\text{-}induced\ sales\ pressure}_{i,t} + \gamma \times \boldsymbol{X}_{i,t} + \mu_k + \theta_c + \delta_t \varepsilon_{k,t} \quad (6)$$

where ***Brown peer-induced flow pressure***, captures trading by investment funds that were already experiencing significant peer outflow pressure. Following Falato et al. (2021 JF), we calculate this variable at the equity issuer-level, which is defined as:

$$Brown\ peer\text{-}induced\ flow\ pressure_{i,t} = \frac{Peer\text{-}induced\ buys_{i,t} - Peer\text{-}induced\ sales_{i,t}}{Shares\ outstanding_{i,t}}$$

$$Peer\text{-}induced\ buys_{i,t} = \sum_j \left(\max(0, \Delta Holdings_{i,j,t}\right) |\ Brown\ peer\ pressure_{j,t} > Percentile\ (90th)$$

$$Peer\text{-}induced\ sales_{i,t} = \sum_j \left(\max(0, -\Delta Holdings_{i,j,t}\right) |\ Brown\ peer\ pressure_{j,t} < Percentile\ (10th)$$

(7)

where i=firm, j=fund, t=time. Vector $\boldsymbol{X}$ include various control variables, such as profitability, leverage, size, Tobin's q, annual returns, and stock-level measure of illiquidity. We also include fixed effects for country (θ_c), industry (μ_k) and time (δ_t).

[Insert Table 7 here]

Table 7 reports the results for stock volatility (Panel A) and stock returns (Panel B). Across both specifications, we see that fund spillovers affect stock volatility and returns for brown industries, although there is limited evidence when it comes to non-brown industries. These findings are intuitive because flow-driven peer pressure is based on similarity in the brown part of fund portfolios, which implies that any second-round impacts from correlated sales will affect the brown stocks. To assess the economic impact, we follow Chernenko and Sunderam (2020) and benchmark our results against the impact on excess volatility induced by fund trading beyond that determined by news about stock fundamentals.

Other control variables are shown to affect equity volatility in a way consistent with the findings in the existing literature. For instance, larger and more profitable firms have lower

volatility, and stocks that are more illiquid and that have lower charter value have higher volatility.

4 Conclusion

This paper provides empirical evidence on how climate risks can amplify financial instability through the interconnectedness of investment funds. By introducing a novel measure of portfolio similarity based on exposure to carbon emission-intensive – "brown" – assets, we find that funds with higher climate risk exposures are more vulnerable to outflows, which lead to disproportionate sales of brown assets. These sales create spillovers to peer funds with similar portfolios, triggering correlated trading behaviour that could amplify systemic risks during episodes of elevated market uncertainty. Furthermore, this spillover effect extends to the real economy, as increased volatility and valuation losses in brown assets raise the cost of capital for affected firms.

Our findings have several implications for financial regulation and systemic risk monitoring. Regulation should consider more explicitly the role of investment funds, and non-bank financial intermediaries more generally, in propagating climate-related financial shocks. Policies could include enhanced disclosure requirements on climate exposures, more focussed stress testing for system-wide risks due to climate-related exposures, and further work on advancing macroprudential measures to mitigate the pro-cyclicality of fund flows. Systemic risk monitoring frameworks, in turn, could benefit from accounting for the clustering of portfolio similarities among funds, as such interlinkages can exacerbate the effects of abrupt climate shocks.

Gaining a more comprehensive understanding of the channels through which climate shocks propagate remains a key policy objective. Further work is needed to examine how differing investor beliefs, time horizons, and regulatory environments influence the pricing of climate risks and the behaviour of financial intermediaries. Such research would contribute to designing more robust frameworks for managing climate risks and ensuring the resilience of the financial system.

References

Bank for International Settlements (2018). BIS Quarterly Review, December.

Bolton, P., & Kacperczyk, M. (2021). "Do investors care about carbon risk?", *Journal of Financial Economics*, *142*(2), 517-549.

Bolton, P., & Kacperczyk, M. (2023). Global pricing of carbon-transition risk. *The Journal of Finance*, *78*(6), 3677-3754.

Brown, O., Froggatt, A., Gozak, N., Katser-Buchkovska, N., & Lutsevych, O. (2023), The consequences of Russia's war on Ukraine for climate action, food supply, and energy security, September.

Chen, H., Joslin, S., & Tran, N. K. (2012). Rare disasters and risk sharing with heterogeneous beliefs. *The Review of Financial Studies*, *25*(7), 2189-2224.

Chen, Q., Goldstein, I., & Jiang, W. (2010). Payoff complementarities and financial fragility: Evidence from mutual fund outflows. *Journal of Financial Economics*, *97*(2), 239-262.

Chernenko, S., & Sunderam, A. (2020). Do fire sales create externalities?. *Journal of Financial Economics*, *135*(3), 602-628.

Choi, D., Gao, Z., & Jiang, W. (2020). Attention to global warming. *The Review of Financial Studies*, *33*(3), 1112-1145.

Coval, J., & Stafford, E. (2007). Asset fire sales (and purchases) in equity markets. *Journal of Financial Economics*, *86*(2), 479-512.

Deng, M., Leippold, M., Wagner, A.F., & Wang, Q. (2022) Stock Prices and the Russia-Ukraine War: Sanctions, Energy and ESG, Swiss Finance Institute Research Paper No. 22-29.

European Supervisory Authorities and European Central Bank (2024). Fit-for-55 climate scenario analysis, November.

Falato, A., Hortacsu, A., Li, D., & Shin, C. (2021). Fire-sale spillovers in debt markets. *The Journal of Finance*, *76*(6), 3055-3102.

Federal Reserve Board (2024). Pilot Climate Scenario Analysis Exercise – Summary of participants' risk management practices and estimates, May.

Financial Stability Board (2021). Financial Stability surveillance framework, September.

——— (2022). Supervisory and regulatory approaches to climate-related risks, final report to the G20, October.

——— (2025). Assessment of climate-related vulnerabilities: analytical framework and toolkit, January.

Financial Stability Board & Network for Greening the Financial System (2022). Climate scenario analysis by jurisdictions: Initial findings and lessons, November.

Gao, G. P., Gao, P., & Song, Z. (2018). Do hedge funds exploit rare disaster concerns?. *The Review of Financial Studies*, *31*(7), 2650-2692.

Georg, C-P., Pierret, D., & Steffen, S. (2024) Similar investors. SSRN working paper.

Giglio, S., Maggiori, M., Stroebel, J., & Utkus, S. (2021). Five facts about beliefs and portfolios. *American Economic Review*, *111*(5), 1481-1522.

Girardi, G., Hanley, K. W., Nikolova, S., Pelizzon, L., & Sherman, M. G. (2021). Portfolio similarity and asset liquidation in the insurance industry. *Journal of Financial Economics*, *142*(1), 69-96.

Goetzmann, W. N., Kim, D., & Shiller, R. J. (2016). *Crash beliefs from investor surveys* (No. w22143). National Bureau of Economic Research.

Goldstein, I., Kopytov, A., Shen, L., & Xiang, H. (2024). Bank heterogeneity and financial stability. *Journal of Financial Economics*, *162*, 103934.

Hsu, P. H., Li, K., & Tsou, C. Y. (2023). The pollution premium. *The Journal of Finance*, *78*(3), 1343-1392.

IMF (2023), Non-bank financial intermediaries: Vulnerabilities amid tighter financial conditions, *Global Financial Stability Report*, April.

Khametshin, D., & Srinivasan, K. (2024). When Banks Herd: Commonality in Sovereign Debt Holdings and Its Effect on Bond Yields. *Available at SSRN*.

Krueger, P., Sautner, Z., & Starks, L. T. (2020). The importance of climate risks for institutional investors. *The Review of Financial Studies*, 33(3), 1067-1111.

Ma, Y., Xiao, K.& Zeng,Y. (2022). Mutual fund liquidity transformation and reverse flight to liquidity. *The Review of Financial Studies*, 35(10), 4674-4711.

Morris, S., Shin, I. & Shin, H. S. (2017). Redemption risk and cash hoarding by asset managers. *Journal of Monetary Economics*, 89, 71-87.

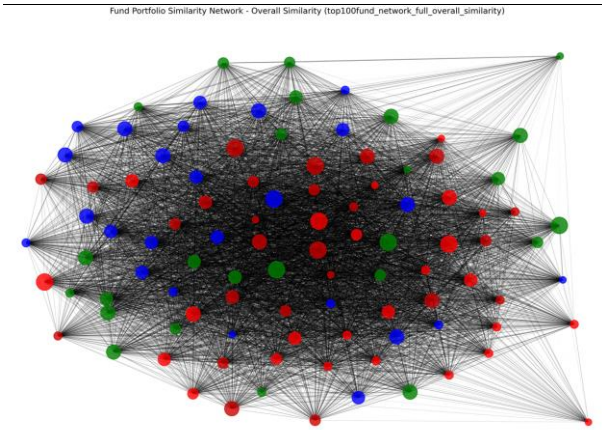
Pástor, Ľ., Stambaugh, R. F., & Taylor, L. A. (2021). Sustainable investing in equilibrium. *Journal of financial economics*, *142*(2), 550-571.

Zhang, S. (2024). Carbon returns across the globe. *The Journal of Finance*.

Figures

Figure [1]: Network graphs showing network linkages among top-100 investment funds by AuM due to their security holdings. Each dot represents a fund, the colours represent the brown share of the funds. The sample is divided in quartiles, being red/dark red those with a brown share above 75th percentile, blue for those where the brown share is between the 25th and 75th percentile, and green for those where brown share is below the 25th percentile. The size of the dots represents the size of the funds per their assets under management. The lines and the position of the dots represent the similarity measure depicted in each graph, overall similarity for Panel A and brown similarity for Panel B.

A. Portfolio similarity



B. Brown similarity

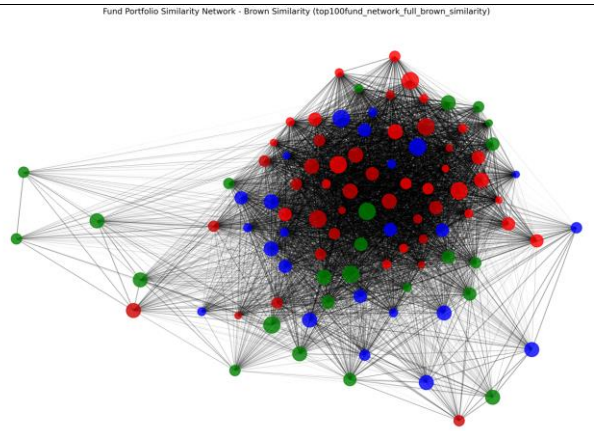


Figure 2 – Panel A: Distribution of emissions intensity (Scope 1+2) across S&P industries in 2021 (end of sample period). Panel A presents emissions intensity by industry, which is calculated as the sum of emissions for all firms in that industry scaled by industry revenue. Industries with emissions intensity exceeding 75th percentile are classified as **brown**.

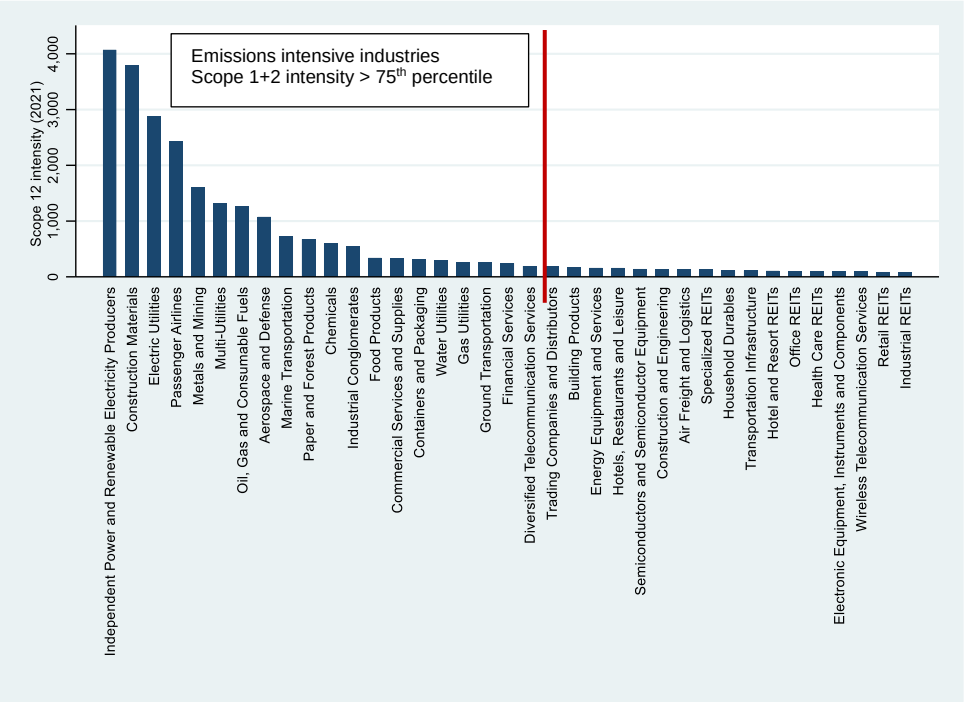


Figure 2 – Panel B presents emissions intensity by industry, which is calculated as the sum of emissions for all firms in that industry scaled by industry revenue. Industries with emissions intensity under the 25th percentile are classified as **green**.

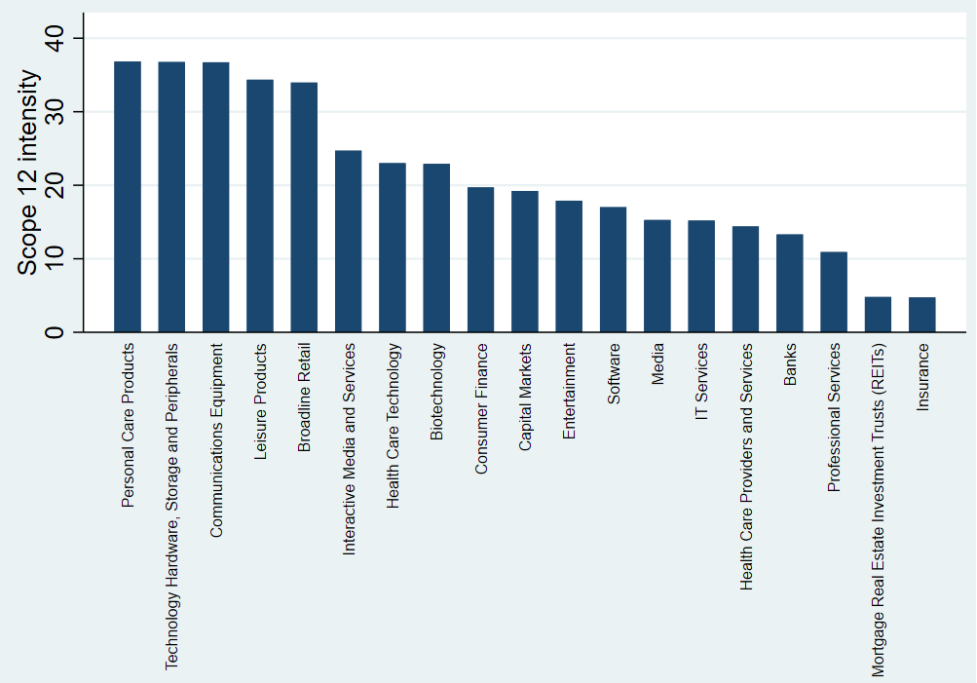


Figure 3: This panel shows the distribution of fund-level exposures to climate risks over the sample period. Time = 0 corresponds to 2016Q1 and time = 23 corresponds to 2021Q4. Bottom panel shows the cross-sectional distribution for 2016 Q1. Dots at the top-end represent funds with the highest exposure to climate risks.

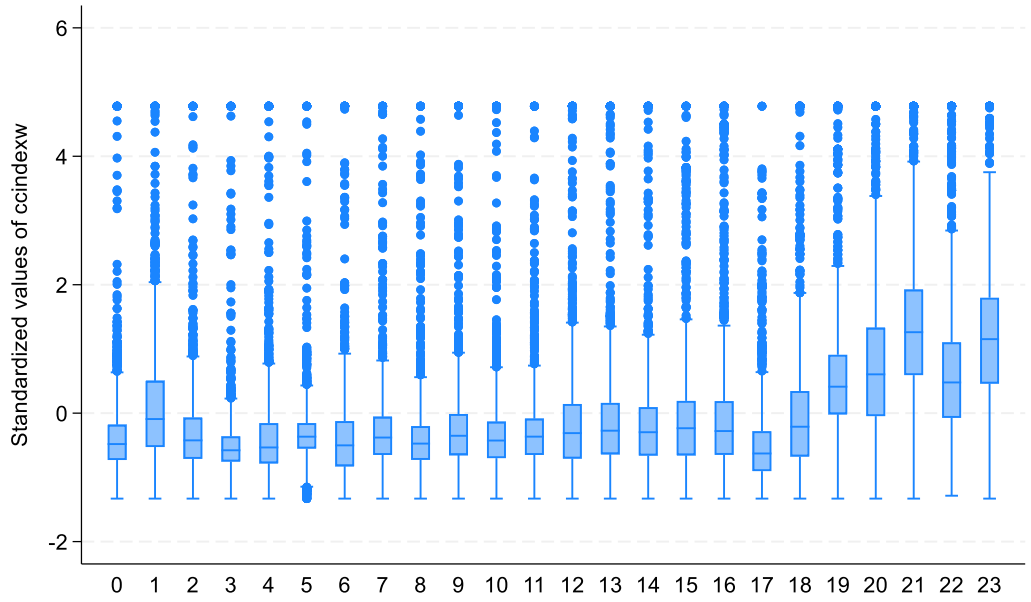


Figure 1: Illustrating difference between similarity and brown share using a three-fund sample. Data for Q3 2019. Panel A shows the portfolio allocation to different industries and Panel B shows the cosine similarity of their brown holdings.

A. Funds allocation to brown industries, in per cent, and Brown share of portfolio

Brown industry	Fund 1	Fund 2	Fund 3
2	0.087	0.038	0.052
3	0.010	0.011	0.014
4		0.006	
6		0.004	0.003
7			0.005
12		0.013	
18		0.003	
20		0.008	0.020
63	0.034	0.021	0.028
65	0.015	0.004	
67	0.005		
Brown share	0.151	0.096	0.122
% in green industries	0.31	0.29	0.28
% in neutral industries	0.39	0.50	0.48
Fund size (aum, USD mln)	5148	6484	11911

B. Funds' pair brown similarity

Fund pair		Brown similarity
Fund 1	Fund 2	0.95
Fund 1	Fund 3	0.09
Fund 2	Fund 3	0.97

Figure 5: Aggregate trading patterns. Panel A depicts the share of funds engaging in net selling/buying in a given quarter. Panel B illustrates the corresponding total US dollar equivalent amounts sold/purchased.

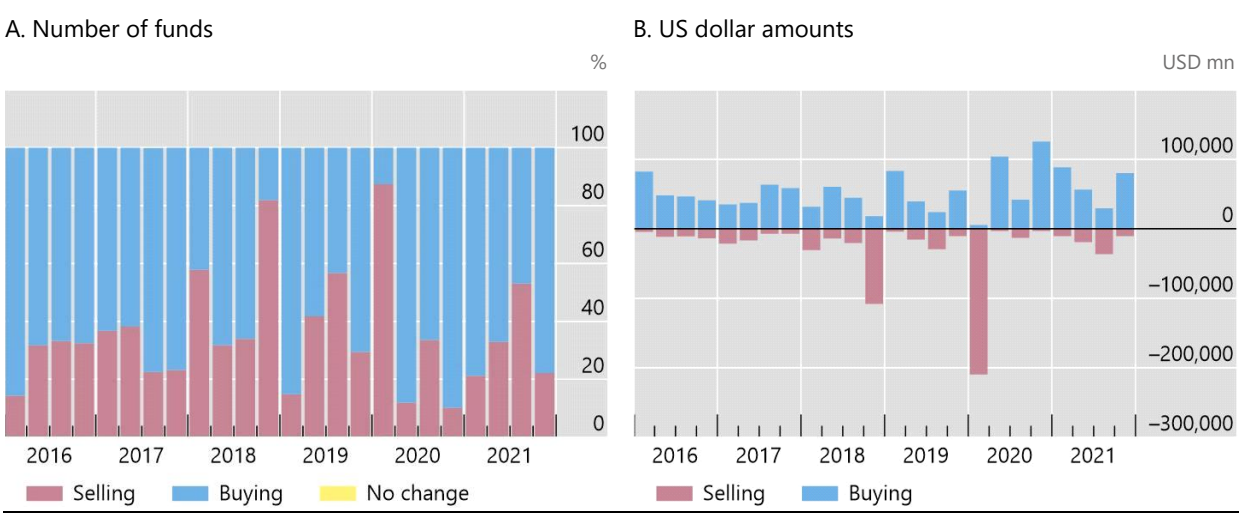


Figure 6: Trading by asset category. Panel A depicts the share of funds engaging in net selling/buying of brown assets in a given quarter. Panel B illustrates the corresponding shares for trading in green assets. Panel C presents the corresponding total US dollar equivalent amounts sold/purchased.

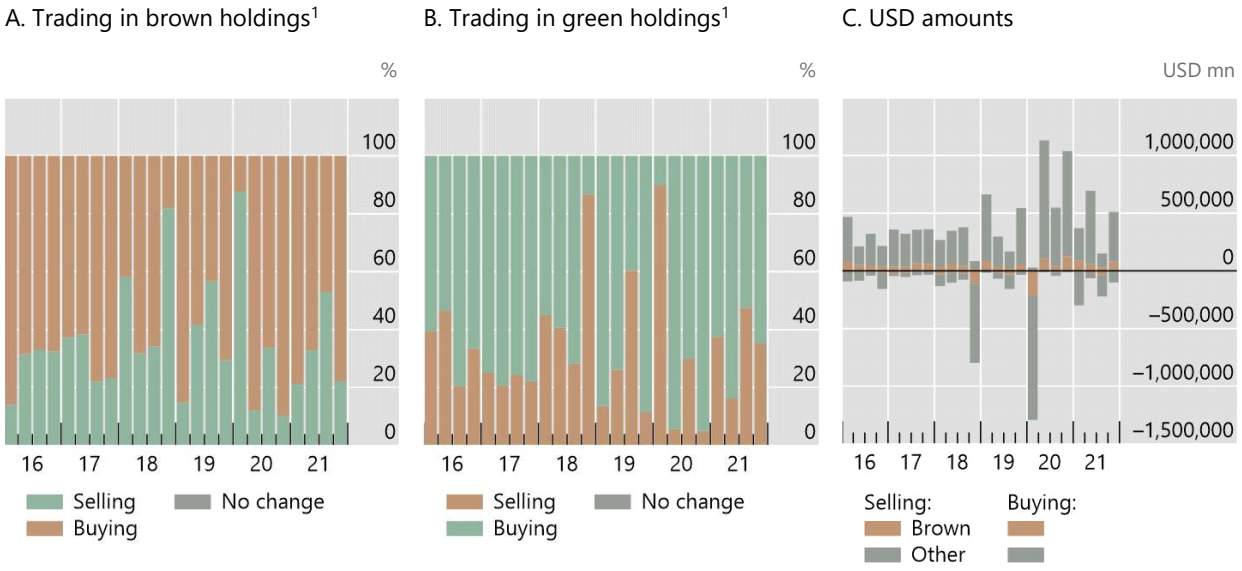


Figure 2: Common sales. This figure shows the average of the natural logarithm of one plus quarterly common sales over the sample period for the full sample and for only large fund pairs.

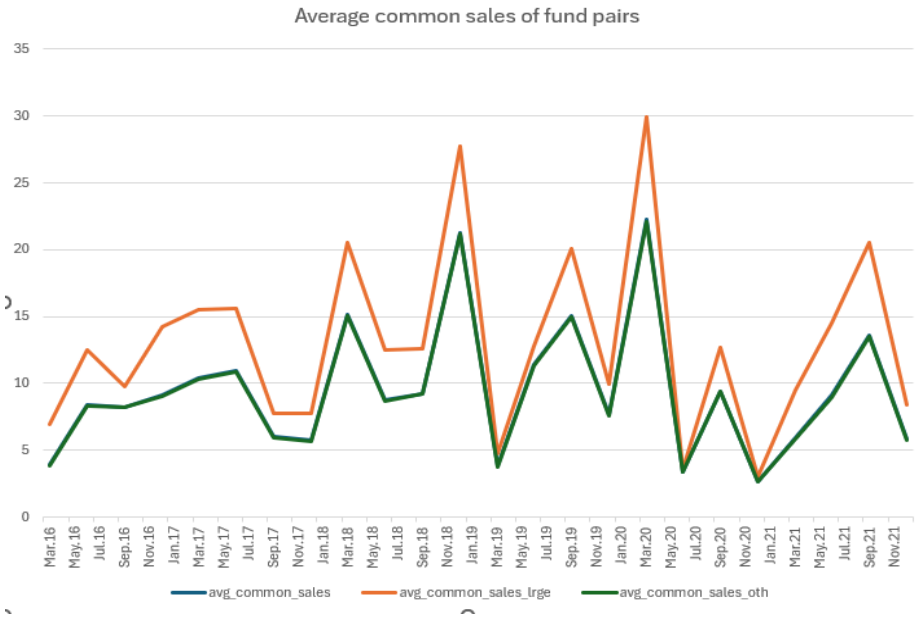


Figure 8: Illustrative example of three fund pairs with differing levels of common sales and brown similarity.

A. Funds sales of brown industries' holdings, in USD millions

Brown industry	Fund 1	Fund 2	Fund 3
2	-	71	-
3	- 13	- 20	- 24
4	-	-	-
6	-	- 1	- 37
7	-	-	- 36
12	-	- 5	-
18	-	-	-
20	-	- 16	-
63	-	-	-
65	-	-	-
67	-	-	-
Brown share	0.151	0.096	0.122
Sales in green industries	- 207	- 160	- 123
Sles in in neutral industries	- 207	- 162	- 125
Fund size (aum, USD mln)	5148	6484	11911

B. Funds' pair brown similarity

Fund pair	Comon sales, dot product	Brown similarity
Fund 1 Fund 2	251,000,000,000,000	0.9492021
Fund 1 Fund 3	307,000,000,000,000	0.0895192
Fund 2 Fund 3	511,000,000,000,000	0.9697224

Table 1: Summary statistics.

Panel A: Fund-level variables	Obs	Mean	10th percentile	50th percentile	90th percentile	Std Dev
Fund Flows	65,828	-0.545	-8.328	-2.142	6.525	14.162
Fund volatility	65,828	1.060	0.516	.887	1.733	0.651
Fund size (log of AuM)	65,828	5.519	3.254	5.540	7.756	1.773
Fund age	65,828	229.083	60	226	383	138.753
Tracking error	65,828	0.408	0.144	0.324	0.776	0.291
Fund returns	65,828	0.0584	-2.779	0.039	2.899	2.812
Cash allocation	65,828	1.551	-0.070	0.895	3.990	3.022
Climate Exposure	65,828	0	-0.883	-.249	1.146	1
Peer Flow Pressure	65,828	0	-1.409	.0845	1.055	1
Panel B: Fund-pair level analyses for similarity						
Brown similarity	115,721,679	0.363	0	0.347	0.809	0.316
Portfolio similarity						
Climate index similarity	115,721,679	0.346	0.011	0.314	0.738	0.266
Common change brown holdings	92,046,852	51.59	-16.53	0.105	82.35	323.182
Common sales brown holdings	92,046,852	20.77	0	0	12.57	108.389
Common buys brown holdings	92,046,852	44.42	0	0.0793	54.23	194.274
Product size	11,4321,808	37.12	19.16	35.52	57.18	14.705
Weighted performance	11,0741,425	3.908	-5.142	4.4	14.3	9.487
Weighted tracking error	101,930,779	0.398	0.162	0.33	0.72	.251
Weighted flows	102,568,497	-22.22	-101.9	-7.814	41.17	124.5
Panel C: Stock-level analysis						
Stock returns	91,789	3.308	-18.796	1.730	26.600	19.840
Stock volatility	91,789	2.236	1.146	1.981	3.633	1.088
ROA	91,789	1.082	-0.508	0.915	3.338	2.140
Leverage	91,789	0.717	0.003	0.408	1.713	0.988
Size	91,789	7.439	5.313	7.301	9.787	1.740
Tobin's *q*	91,789	0.691	0.003	0.104	1.687	1.360
Stock illiquidity	91,789					
Peer flow pressure	91,789	0.000	0.097	0.097	0.052	1.000

Table 2: Impact of climate exposure on fund flows and returns. The dependent variable is fund's quarterly flows scaled by lagged AUM in column (1) and fund returns in column (2). The independent variables are lagged by one quarter. "×" denotes interaction between corresponding variables. Fund performance is fund's excess returns relative to median. Panel A shows the baseline results using equation (1), panel B introduces an interaction term between fund similarity and climate exposure, and panel C shows the marginal effects of results for this interaction term. The coefficients for climate exposure have been standardised (mean = 0; std. dev=1). Standard errors clustered at fund-level and p-values are shown in parenthesis.

	(1)	(2)
Panel A: Baseline regressions	Fund Flows	Fund Returns
Fund flows	0.157***	0.002
	(0.000)	(0.142)
Fund volatility	-0.111	-0.627***
	(0.729)	(0.000)
Fund size	-5.834***	-1.026***
	(0.000)	(0.000)
Fund age	-0.025***	-0.014***
	(0.007)	(0.000)
Tracking error	-0.444	-2.616***
	(0.290)	(0.000)
Fund returns	0.303***	
	(0.000)	
Cash holding	0.084***	-0.042***
	(0.002)	(0.000)
Climate exposure	-0.283**	0.323***
	(0.037)	(0.000)
Fund FE	Y	Y
Time FE	Y	Y
Observations	65,828	65,828
R-squared	0.277	0.810
	(1)	(2)
Panel B: Impact of fund similarity on baseline regressions	Fund Flows	Fund Returns
Climate exposure	-0.210	-0.172
	(0.257)	(0.105)
Middle tercile of similarity	-0.183	-0.257***
	(0.315)	(0.001)
Top tercile of similarity	-0.441*	-0.139
	(0.066)	(0.126)
Climate exposure X Middle tercile of similarity	0.124	0.472***
	(0.434)	(0.000)
Climate exposure X Top tercile of similarity	-0.388**	0.994***
	(0.037)	(0.000)
Other controls	Y	Y
Fund FE	Y	Y
Time FE	Y	Y
Observations	65,828	65,828
R-squared	0.278	0.811
Panel C: Marginal effects (at means)		
Climate exposure X Low tercile	-0.654***	3.436***
	(0.133)	(0.057)
Climate exposure X Medium tercile	-0.837***	3.179***
	(0.087)	(0.032)
Climate exposure X Top tercile	-1.094	3.297***
	(0.125)	(0.043)
Panel D: Pairwise test for difference in interaction terms (F-test)		
Climate exposure X Low tercile = Climate exposure X Middle tercile	0.61	14.77***
Climate exposure X Middle tercile = Climate exposure X High tercile	11.93***	28.89***
Climate exposure X Low tercile = Climate exposure X High tercile	4.37**	85.17***

Table 3: Impact of climate exposure on fund-level changes in holdings of cash, brown assets, green assets, and others. The dependent variable in column (1) is change in cash allocation, (2)-(4) is the change in brown/green/other assets in raw $ amount and in (5)-(7) where they are scaled by total fund value. irms are assigned to these broad categories based on whether they belong to brown, green, or other industries.

	(1) Δ Cash allocation / Fund value	(2) Δ MV(Brown Assets)	(3) Δ MV(Other Assets)	(4) Δ MV(Green Assets)	(5) Δ MV(Brown Assets) / Fund value	(6) Δ MV(Other Assets) / Fund value	(7) Δ MV(Green Assets) / Fund value
Fund volatility	18.427***	-1.848**	-3.584	4.296**	-1.879	-4.428	3.457
	(0.000)	(0.024)	(0.266)	(0.021)	(0.392)	(0.570)	(0.456)
Fund size	-3.381***	-0.980***	2.531	3.146***	-19.666***	-92.512***	-51.601***
	(0.004)	(0.002)	(0.112)	(0.003)	(0.000)	(0.000)	(0.000)
Fund age	0.154	-0.273**	-1.406***	-0.888***	0.064	0.391	0.008
	(0.183)	(0.018)	(0.002)	(0.001)	(0.319)	(0.253)	(0.969)
Tracking error	-22.297***	-3.167***	-29.009***	-18.968***	1.920	-42.222***	-29.837***
	(0.001)	(0.007)	(0.000)	(0.000)	(0.512)	(0.000)	(0.000)
Fund returns	1.116***	0.239***	0.706***	0.246**	0.966***	1.802***	1.040***
	(0.003)	(0.000)	(0.000)	(0.042)	(0.000)	(0.000)	(0.000)
Cash holding		0.351***	1.517***	1.002***	1.174***	4.123***	2.673***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Climate exposure	-0.953	1.644***	-3.641***	0.880	4.883***	-15.867***	-1.758
	(0.588)	(0.000)	(0.002)	(0.292)	(0.000)	(0.000)	(0.346)
Fund flows	-0.304***	**0.064*** **	**0.262*** **	**0.154*** **	**0.240*** **	**1.048*** **	**0.633*** **
	(0.000)	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**
Fund flows X Climate exposure	-0.000	**0.026*** **	**0.015**	**-0.025***	**0.107** **	**0.023**	**-0.051**
	(0.995)	**(0.006)**	**(0.499)**	**(0.085)**	**(0.021)**	**(0.847)**	**(0.379)**
Fund FE	Y	Y	Y	Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y	Y	Y
Observations	64,454	62,908	62,908	62,908	62,908	62,908	62,908
R-squared	0.025	0.177	0.280	0.277	0.188	0.286	0.273

Table 4: Impact of climate exposure on fund flows: Robustness checks. The outputs shown here replicate results from column (1) of Table 2 with additional controls. Column (1) of Panel A controls for time-varying factors that could affect funds' investment strategy using Geography X Time FE and column (2) includes controls for future fund returns (up to next four quarters). Panel B uses cross-sectional regression to show the predictive power of climate exposure on funds' future flows for different climate and non-climate shocks. Columns show the timestamp for outcome variable. For instance, column (1) of the panel showing results for onset of Russia's invasion of Ukraine shows predictive power of lagged climate exposure on fund flows in Q1-2021. Since Russia invaded Ukraine on 24 February 2022, we see this as the first quarter of our event. Column (2) uses fund flows in Q2-2021 and so on. Standard errors clustered at fund-level and p-values are shown in parenthesis.

	(1)	(2)
Panel A:		
Climate exposure	-0.264*	-0.273*
	(0.055)	(0.050)
Fund FE	Y	Y
Time FE	Y	Y
Geographic Focus X Time FE	Y	
Observations	65,828	59,882
R-squared	0.241	0.253

Table 5: Impact of brown similarity on changes/sales/buys in brown holdings. Based on industry measures of similarity. Columns (4)-(6) use an alternative measure of brown similarity that also accounts for the climate exposure of each industry that the fund has invested in (and not just the ones that have been identified as brown). All fund-level covariates (weighted performance and tracking error) are computed at fund-par level, weighted by AuM. Product size is the product of the AUM of fund pair. variables have been described in the Annex.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Aggregate changes		Aggregate sales		Aggregate buys		Aggregate changes	Aggregate sales	Aggregate buys
Brown similarity	37.469***	38.043***	32.748***	33.079***	1.646**	1.746**	34.775***	31.131***	1.939***
	(2.087)	(2.131)	(1.183)	(1.208)	(0.720)	(0.732)	(1.900)	(1.134)	(0.700)
Brown Similarity X Weighted Flows							-0.141***	-0.084***	0.008
							(0.023)	(0.009)	(0.011)
Weighted flows		-0.078***		0.082***		-0.166***	-0.016	0.119***	-0.170***
		(0.027)		(0.009)		(0.019)	(0.030)	(0.010)	(0.020)
Product size of funds pair	8.905***	8.874***	3.339***	3.443***	7.519***	7.383***	8.875***	3.445***	7.383***
	(0.534)	(0.530)	(0.186)	(0.185)	(0.416)	(0.408)	(0.530)	(0.185)	(0.408)
Weighted performance	-0.386*	-0.604***	0.658***	0.665***	-0.605***	-0.758***	-0.607***	0.666***	-0.758***
	(0.214)	(0.215)	(0.075)	(0.077)	(0.141)	(0.143)	(0.215)	(0.077)	(0.143)
Weighted tracking error	-9.382	-6.927	-4.162**	-4.531**	-0.382	2.202	-6.597	-4.332**	2.183
	(5.814)	(6.014)	(2.104)	(2.165)	(4.665)	(4.804)	(6.009)	(2.162)	(4.805)
Common change/sales/buys in holdings, mln	-0.020***	-0.021***	-0.054***	-0.054***	0.005*	0.004	-0.021***	-0.055***	0.004
	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)
Fund-pair FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Time and Fund FE separately	Y	Y	Y	Y	Y	Y	Y	Y	Y
SE Cluster at both funds separately	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	73,634,548	69,729,321	73,634,548	69,729,321	73,634,548	69,729,321	69,729,321	69,729,321	69,729,321
R-squared	0.439	0.438	0.601	0.599	0.571	0.573	0.438	0.599	0.573
Avg (Y-var)	53.66		22.48		44.92				
Median (Y-var)	0.133		0		0.083				

s

Table 6: Analysis of fund flows and spillover effect from peer flow pressure. This table reports regressions of fund flows in columns (1)-(6) and fund returns in column (7) and a dummy=1 if fund returns are below 10th percentile in column (8). The variable of interest is peer flow pressure that proxies for pressure induced by flows in peer funds (Brown peer pressure – see Annex B). Fund climate exposure is computed as the weighted average of climate exposure of fund's portfolio constituents, where weights correspond to the portfolio weights. Higher climate index implies greater exposure to climate uncertainty. All other variables are described in annex table. Values shown in brackets are p-values. Standard errors are clustered at fund-level.

	Fund flows						Fund returns	Extreme fund returns (left tail)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
		Baseline	With Standardised coefficients	25th percentile	10th percentile	5th percentile		
Fund flow	0.288***	0.156***	2.215***	0.180***	0.111***	0.109***	0.002	0.001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.192)	(0.141)
Std. Dev of fund returns	-0.430*	-0.110	-0.072	-0.977***	-1.302***	-1.496***	-0.603***	0.048***
	(0.071)	(0.731)	(0.731)	(0.000)	(0.001)	(0.009)	(0.000)	(0.000)
Fund size	-0.543***	-5.842***	-10.357***	0.114***	0.392***	0.943***	-1.030***	0.048***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Fund age	-0.007***	-0.026***	-3.554***	0.001***	0.005***	0.009***	-0.014***	-0.000
	(0.000)	(0.006)	(0.006)	(0.000)	(0.000)	(0.000)	(0.000)	(0.734)
Tracking error	0.857***	-0.471	-0.137	-1.068***	-3.188***	-5.220***	-2.642***	0.167***
	(0.001)	(0.262)	(0.262)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Fund returns	0.359***	0.302***	0.851***	0.153***	0.257***	0.338***	0.022**	-0.001*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.025)	(0.091)
Cash allocation	0.012	0.084***	0.254***	0.004	0.033	0.060	-0.042***	0.002***
	(0.544)	(0.002)	(0.002)	(0.714)	(0.355)	(0.229)	(0.000)	(0.007)
Brown peer pressure	0.091	0.186**	0.186**	0.175***	0.573***	0.816***	0.159***	-0.010***
	(0.349)	(0.048)	(0.048)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Fund climate exposure	0.089	-0.267**	-0.267**	-0.049	-0.069	-0.165	0.336***	0.001
	(0.273)	(0.049)	(0.049)	(0.244)	(0.620)	(0.456)	(0.000)	(0.975)
Fund FE		Y	Y	Y	Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y	Y	Y	Y
Observations	65,828	65,828	65,828	65,828	65,828	65,828	65,828	65,828
R-squared	0.137	0.277	0.277	0.101	0.025	0.003	0.810	0.138

Table 7: Analysis of equity volatility (Panel A) and returns impact (Panel B). This table reports regressions of stock volatility, computed using standard deviation of quarterly equity returns, on a variable that proxies for trades due to peer flow pressure (see Annex C). Equity returns are computed using the quarterly changes in stock price. ROA is net income to total assets. Leverage is debt to equity ratio. Tobin's q is the market to book value of assets, where market value of assets is the sum of market value of equity and book value of debt. Amihud's illiquidity measure is the annual average ratio of the absolute daily return to the daily dollar transaction volume. Brwon peer-induced flow pressure as defined above. Standard errors are clustered at country-level.

Panel A: Stock volatility	(1) Country FE	(2) Country and Ind FE	(3) Standardised all X variables	(4) Only Brown Industries	(5) Only Non-brown Industries	(6) 90th percentile	(7) 75th percentile	(8) 50th percentile
Equity returns	0.004***	0.004**	0.070**	0.006***	0.003**	0.005***	0.005***	0.005***
	(0.009)	(0.016)	(0.016)	(0.000)	(0.045)	(0.000)	(0.001)	(0.000)
ROA	-0.059**	-0.054***	-0.115***	-0.054***	-0.057**	-0.083***	-0.061*	-0.041
	(0.032)	(0.010)	(0.010)	(0.004)	(0.046)	(0.001)	(0.082)	(0.230)
Leverage	0.095***	0.124***	0.123***	0.092***	0.099***	0.170***	0.117***	0.074***
	(0.000)	(0.000)	(0.000)	(0.002)	(0.000)	(0.000)	(0.001)	(0.000)
Size	-0.172***	-0.139***	-0.243***	-0.173***	-0.174***	-0.259***	-0.197***	-0.137***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Tobins q	-0.019	0.035***	0.047***	0.338**	-0.030	0.061	0.017	0.006
	(0.420)	(0.009)	(0.009)	(0.012)	(0.156)	(0.476)	(0.712)	(0.788)
Amihud's illiquidity	0.137***	0.151***	0.085***	0.176***	0.115***	0.171***	0.068	0.024
	(0.000)	(0.000)	(0.000)	(0.003)	(0.000)	(0.006)	(0.302)	(0.649)
Brown peer-induced flow pressure	0.019***	0.017***	0.017***	0.024***	0.017**	0.037***	0.029***	0.012**
	(0.006)	(0.003)	(0.003)	(0.004)	(0.015)	(0.000)	(0.000)	(0.016)
Time FE	Y	Y	Y	Y	Y	Y	Y	Y
Country FE	Y	Y	Y	Y	Y			
Industry FE		Y	Y					
Observations	91,789	91,789	91,789	16,652	75,137	91,789	91,789	91,789
R-squared	0.327	0.371	0.371	0.352	0.335	0.268	0.271	0.268

Table 7 (continued)

Panel B: Stock returns	(1) Country FE	(2) Country and Ind FE	(3) Only Brown Industries	(4) Only Non-brown Industries	(5) 10th percentile	(6) 25th percentile	(7) 50th percentile
Equity volatility	0.633***	0.391**	1.052***	0.420**	-4.238***	-2.701***	-0.347*
	(0.001)	(0.025)	(0.003)	(0.016)	(0.000)	(0.000)	(0.090)
ROA	0.902***	0.912***	1.279***	0.842***	0.801***	0.860***	1.003***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Leverage	0.329***	0.472***	0.612***	0.322***	-0.084	-0.025	0.266***
	(0.000)	(0.000)	(0.007)	(0.000)	(0.511)	(0.801)	(0.001)
Size	-0.157*	-0.066	-0.244**	-0.208*	0.329***	0.226*	0.049
	(0.060)	(0.283)	(0.013)	(0.054)	(0.006)	(0.071)	(0.578)
Tobins q	0.440***	0.818***	3.924***	0.385***	0.874***	0.743***	0.628***
	(0.001)	(0.000)	(0.000)	(0.000)	(0.002)	(0.000)	(0.000)
Amihud's illiquidity	0.331	0.402*	0.597*	0.146	-0.295	0.073	-0.166
	(0.157)	(0.062)	(0.082)	(0.501)	(0.337)	(0.825)	(0.538)
Brown peer-induced flow pressure	0.019	0.010	-0.382***	-0.065	-0.126	-0.120	-0.103
	(0.850)	(0.918)	(0.009)	(0.549)	(0.295)	(0.188)	(0.279)
Time FE	Y	Y	Y	Y	Y	Y	Y
Country FE	Y	Y	Y	Y			
Industry FE		Y					
Observations	91,787	91,787	16,652	75,135	91,787	91,787	91,787
R-squared	0.212	0.216	0.234	0.212	0.129	0.161	0.201

Annex

Table A1: Variable definitions and sources

Variable	Definition	Source
Fund flows	Quarterly flows – primary fund level (taking into account share classes)	Lipper
Fund volatility	Standard deviation of fund returns	Lipper
Fund returns	Quarterly fund's excess returns relative to median - primary fund level (taking into account share classes)	Lipper
Fund size	Quarterly fund size in terms of AUM – primary fund level (taking into account share classes)	Lipper
Fund age	Months since inception of the fund	Lipper
Tracking error (performance)	Quarterly standard deviation of fund's excess returns from benchmark– primary fund level (taking into account share classes)	Lipper
Cash allocation	Quarterly % of portfolio allocated to cash - primary fund level (taking into account share classes)	Lipper
Brown similarity	The similarity for the brown part of the portfolio. Calculated as the weighted average of a fund's portfolio similarity with all others following Girardi et al. (2021, JFE) and the weights used correspond to the brown share of the peer funds	Lipper and S&P Capital IQ
Common change / sales / buys (brown holdings)	a) first calculating the change in holdings from brown industries; b) then with the matrix of the holdings of each fund x brown industry x quarter we calculate the similarity of the changes in positions for each fund pair and quarter; c) to construct the measure of common changes, we follow Girardi et al. (2021), and calculate the dot product of the pair's portfolio weight vectors normalized by the vectors' lengths.	Lipper and S&P Capital IQ
Climate exposure	Computed as the weighted-average climate exposure of the investment fund based on climate exposure of investee industries, where weights = portfolio weights. Climate exposure of industries is based on the index in Sautner et al. (2023 JF).	S&P Capital IQ and
Climate index similarity	Similarity in fund pairs of the common exposure of both funds to climate shocks. Following Girardi et al. (2021 JFE).	S&P Capital IQ and
Aggregate Climate index similarity	Same as above but multiplying the similarity by the dot product of climate exposures of fund1 and fund2 using weights to industry exposures.	S&P Capital IQ and
Illiquidity	(Bid-Ask)/mid-price * 100	

Table A2: Determinants of brown similarity.

	(1) portfolio similarity	(3) portfolio similarity	(4) brown similarity	(6) brown similarity	13) portfolio similarity	(15) portfolio similarity	(16) brown similarity	(18) brown similarity
Size (weighted avg)	0.002***	0.002***	0.002***	0.002***	0.001***	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Performance (wt avg)	0.000***	0.000***	-0.001***	-0.001***	0.001***	0.001***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Tracking error (wt avg)	-0.187***	-0.187***	-0.188***	-0.188***	-0.013***	-0.013***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Brown share (wt avg)	-0.154***	-0.154***	0.386***	0.386***	-0.025***	-0.025***	0.218***	0.218***
	(0.001)	(0.001)	(0.003)	(0.003)	(0.001)	(0.001)	(0.005)	(0.005)
Green share (wt avg)		0.002***		0.001***		0.000***		0.000***
		(0.000)		(0.000)		(0.000)		(0.000)
Dummy=1 if large pair	0.001**	0.001**	0.007***	0.007***				
	(0.001)	(0.001)	(0.001)	(0.001)				
Dummy=1 if global focus	0.026***	0.026***	0.020***	0.020***				
	(0.000)	(0.000)	(0.001)	(0.001)				
Dummy=1 if US focus	0.025***	0.025***	-0.003***	-0.003***				
	(0.000)	(0.000)	(0.000)	(0.000)				
Dummy=1 if EME focus	0.291***	0.291***	0.168***	0.168***				
	(0.001)	(0.001)	(0.002)	(0.002)				
Time FE	YES	YES	YES	YES	YES	YES	YES	YES
Fund FE					YES	YES	YES	YES
Observations	93,551,104	93,551,104	93,551,104	93,551,104	93,468,233	93,468,233	93,468,233	93,468,233
R-squared	0.074	0.075	0.039	0.039	0.907	0.907	0.698	0.698
R2-Overall	0.0744	0.0746	0.0395	0.0395	0.907	0.907	0.698	0.698

Table A3: Impact of brown similarity on changes/sales/buys in brown holdings. Columns (1)-(3) based on industry brown similarity that also accounts for the climate exposure of each industry that the fund has invested in (and not just the ones that have been identified as brown). Columns (4)-(6) uses ISIN-based measure of brown similarity. All fund-level covariates (weighted performance and tracking error) are computed at fund-pair level, weighted by AuM. Product size is the product of the AUM of fund pair. variables have been described in the Annex.

	Aggregate climate index similarity (industry-based)			ISIN-based measure of brown similarity		
	(1)	(2)	(3)	(4)	(5)	(6)
	Aggregate changes	Aggregate sales	Aggregate buys	ISIN changes	ISIN sales	ISIN buys
Brown similarity	6.378***	4.517***	0.573***	2.511***	2.118***	1.222***
	(0.421)	(0.205)	(0.152)	(0.089)	(0.048)	(0.057)
Common change/sales/buys	-0.020***	-0.054***	0.005*	0.018***	-0.035***	0.034***
in holdings, mln	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)	(0.003)
Product size of funds pair	8.927***	3.362***	7.519***	0.003**	0.003***	0.002*
	(0.535)	(0.186)	(0.416)	(0.001)	(0.000)	(0.001)
Weighted performance	-0.394*	0.651***	-0.605***	-0.001***	0.000	0.000
	(0.215)	(0.075)	(0.141)	(0.001)	(0.000)	(0.001)
Weighted tracking error	-9.039	-3.820*	-0.379	0.126***	-0.050***	0.189***
	(5.818)	(2.105)	(4.665)	(0.021)	(0.009)	(0.026)
Fund-pair FE	Y	Y	Y	Y	Y	Y
Time and Fund FE separately	Y	Y	Y	Y	Y	Y
SE Cluster at both funds separately	Y	Y	Y	Y	Y	Y
Observations	73,634,548	73,634,548	73,634,548	90,472,748	90,472,748	90,472,748
	0.439	0.600	0.571	0.377	0.405	0.453