

Non-banks contagion and the uneven mitigation of climate risk

Régis Gourdel 

Vienna University of Economics and Business

Matthias Sydow

European Central Bank

July 2023

We thank Irene Monasterolo for her comments on earlier versions of the manuscript, an anonymous referee for the ECB Working Paper Series for their suggestions, participants of the “Steering Financial Markets in the Sustainable Transition” conference and of the ECB Climate Change Centre seminar series for their constructive questions and comments.

RG acknowledges the financial support of the Erasmus+/Knowledge Alliance project [GrEnFin, grant number 612408-EPP-1-2019-1-EPPKA2-KA], and the technical support of the European Central Bank. Any views expressed are those of the authors alone and do not necessarily represent the views of the ECB or the Eurosystem.

Contact details: regis.gourdel@wu.ac.at, matthias.sydow@ecb.europa.eu

Abstract

This paper develops a framework for the short-term modelling of market risk and shock propagation in the investment funds sector, including bi-layer contagion effects through funds' cross-holdings and overlapping exposures. Our work tackles chiefly climate risk, with a first-of-its-kind dual view of transition and physical climate risk exposures at the fund level. So far, while fund managers communicate more aggressively about their awareness of climate risk, it is still poorly assessed. Our analysis shows that the topology of the fund network matters and that both contagion channels are critical in its study. A stress test based on granular short-term transition shocks suggests that the differentiated integration of sustainability information by funds has made network amplification less likely, although first-round losses can be material. On the other hand, there is room for fund managers and regulators to consider physical risk better, and mitigate the second-round effects it induces, as these are less efficiently absorbed by investment funds. Improving transparency and setting relevant industry standards in this context would help mitigate short-term financial stability risks.

JEL codes: C62, G23, G17, Q54.

Keywords: climate finance, investment funds, systemic risk, stress testing.

Non-technical summary

Investment funds have reached an important size within the financial sector, but their regulation or efforts to stress test them has so far lagged behind the efforts made on banks. In this paper, we develop a framework allowing for their stress testing in a short-term time frame, i.e. plausibly unfolding over a few weeks. The core model integrates different steps and is adaptable with regard to the order in which they are combined. Crucially, we capture contagion on two layers with distinct underlying mechanisms. The first one is that of funds' cross-holdings, i.e. the shares of open-end funds that are held by other funds, whose value changes based on the balance sheet of the issuing fund. The second layer is the overlapping exposures on the secondary market of securities, whereby investment funds can be exposed to common shocks, but can also impact one another by influencing prices through sales and purchases. The model allows for market shocks, i.e. changes in the values of traded securities, as well as liquidity shocks coming from redemptions by investors.

Our application tackles in particular climate risk, which consists of both transition risk (exposure to shocks induced by climate change mitigation) and physical risk (exposure to assets susceptible to destruction or value loss from extreme weather events or evolving climate conditions). So far, while the sector has set itself some targets with regard to this problem, the risk is still poorly assessed. We leverage on several proprietary data sets covering climate-related variables for the real economy, and investment funds balance sheets. The data set that we assemble provides a first-of-its-kind dual view of transition and physical climate risk exposures at the fund level. Our analysis shows that the topology of the fund network matters and that both contagion channels are important in its study, although few funds present a high-risk profile for both of them. Moreover, climate risk seems unequally integrated, with transition risk strongly mitigated or exacerbated by the specialization strategies adopted for some fund portfolios, but very little dispersion in physical-risk profiles.

A stress test on the basis of granular short-term transition shocks suggests that the differentiated integration of sustainability information by funds has made network amplification of climate transition shocks less likely, although first-round losses can be material. Market shocks, such as tested here, could have important consequences in terms of flows reallocated from high-carbon to low-carbon investment funds, although their timing is more likely to increase financial instability than allowing useful investment in low-carbon sectors. On the other hand, there is room for fund managers and regulators to consider physical risk better and mitigate the second round effects it induces, as they are less efficiently absorbed by investment funds. Improving transparency and setting relevant industry standards in this context would help mitigate short-term financial stability risks.

1 Introduction

The search for ways to stress test investment funds has gained traction due to the growth of the sector and its centrality in the financial system. This drove an expansion of the literature dedicated to estimating the risk posed by investment funds to financial stability [9, 23, 47, 50]. In parallel, investment funds have been increasingly integrated into more complex models to account for their interaction with the financial system at large [45]. This work integrates this broader effort, and the mechanisms it developed are a building block of the work on system-wide stress testing conducted at the European Central Bank [96].

Due to their increased importance in financing the real economy [40], investment funds are positioned as crucial players in the transmission through the financial system of policies to green the economy. Pledges have been made by key members of the industry to better integrate climate risk, either through the use of their voting rights or disinvestment. The sub-sector of ESG and “green” investment funds has grown impressively in the past decade, although its size and technical capacity still do not appear up to the task of steering the financial system to a position in line with climate mitigation objectives [60, 77, 87].

However, the will and capacity of investment funds to tackle climate change are questioned. While financial markets have somewhat adapted to the emergence of climate physical and transition risk, the risk is currently not fully priced [69]. Furthermore, the use of greenwashing by funds to attract investors is a concern for regulatory authorities [16, 30, 62], and for the public interest at large, in taking effective steps toward climate change mitigation [38, 90]. It creates an asymmetry of information between them and their investors, exposing the latter to unexpected shocks related to transition risk. Climate action is also limited so far by an entrenched interest in carbon-intensive industries, as well as a patchy framework when it comes to redirecting investment flows [76]. In particular, structural limitations such as policy uncertainty, lack of transparency, insufficiency of existing guides for green investment, and lack of incentives for fund managers have hampered the adaptation necessary. Thus, Amzallag [5] finds that European funds still significantly overweight “brown” firms in their portfolios on aggregate, and the climate risk of the financial sector remains generally high.¹ One additional concern is the possibility of network externalities, where the presence of large risks associated with climate change could lead to systemic failures [93]. In our application, this general systemic risk concern could add to the climate-specific market failure.

The emergence of climate shocks raises new questions in the particular context of network stress testing, due to the heterogeneity in how different groups of agents are impacted. This is particularly relevant for investment funds, which are often specialized in ways that can correlate with climate risk factors (sector or location), and own a large share of the risk [89]. Thus, it matters to know whether climate shocks are more likely to be only amplified within certain subgroups of nonbanks, or transmitted to the rest of the network, and which of these options would be best at absorbing damages with the least negative externalities. Our contribution to the literature on these questions is threefold:

- (i) We develop a general short-term stress testing framework for investment funds, taking into account both contagion channels of inter-fund holdings and common secondary market exposures.

¹As investment funds appear vulnerable to climate shocks, they were included in the long-term portfolio losses projections of ECB/ESRB [41], which is itself in line with Battiston et al. [13].

- (ii) We build a first-of-its-kind dual climate risk profile for firms and investment funds portfolios, with data on both transition and physical risk exposures.
- (iii) We apply our model to a range of plausible shocks, representing climate-related short-term stress.

This framework is designed to fully capture network externalities and contagion in the investment fund sector. Our model unfolds in three steps, starting with a shock on external asset holdings, allowing for a flexible input. It is followed by a redemption shock, after which liquidity-constrained funds liquidate assets. Our framework can be applied to a variety of narratives, such as extreme weather events, or sudden – and little expected – policy shocks. In a previous exercise, Roncoroni et al. [86] simulate the reaction to climate transition shocks along these lines, relying on a bank-fund system. In addition, we allow redemptions based on initial shocks, which are crucial for funds as they are little leveraged and most exposed to liquidity risk from their liability side. Furthermore, this allows us to integrate the key stylized fact that sustainable funds are less prone to procyclical redemptions than their conventional counterparts [17, 27, 84].

We show how a new price equilibrium between fund shares can form consistently with their equity cross-holdings. Importantly, this captures the evolution of fund shares at each step during which their portfolio of external holdings evolves. This contagion channel is enough of a concern that Veer et al. [99] recommends supervisors to limit funds participation in other investment funds, as it creates an “illusion of liquidity”. Thus, we model shock propagation on two layers: portfolio overlap and direct cross-holdings. The price clearing mechanism is conceptually similar to what is done for network banking models, such that the overall propagation is in line with the literature on stress amplification between banks, occurring through both the interbank market and portfolio overlaps.²

The dynamics that we model are meant to unfold over the space of some weeks – the kind of short-term time frame that was recently called for by the UN Environment Programme Finance Initiative [28] for climate risk. This also corresponds to the narrative of a “climate Minsky moment”, as considered by the IMF [1, 61]. Indeed, the market granularity of our model is precisely compatible with the time frame where network contagion operates, which is generally short-term. In addition, it avoids the distortion of price impact that occurs through coarse aggregations. As we rely on a static balance-sheet hypothesis, our results can be regarded as informative over the medium term following the time of the data used.

We then build an *ex ante* climate risk profile of investment funds that reveals an unequal integration of transition and physical climate risks. Our sample consists of over 23,000 investment funds worldwide, and we rely on security-level climate risk data combined with fund holdings. We find that funds exhibit a strong heterogeneity in their exposure to transition risk, but are more homogeneous with regard to physical risk, i.e. no significant segment of the investment funds sector achieves a clear reduction in its exposure to physical risk. The latter can be explained by a lack of relevant data, lack of awareness of acute physical risk in general, or lack of tools to translate the firms’ exposures into potential losses. Overall, our analysis suggests that investment funds taken globally have a high exposure to both types of risk through portfolio holdings when compared to the general economy. This climate risk profile then interacts with the systemic nature of the funds at the point of realizing

²Examples include Poledna et al. [81], Roncoroni et al. [85], and Wiersema et al. [102], although the counterparty risk transmission channel does not necessarily rely on an Eisenberg and Noe-type clearing mechanism as we do.

the propagation of climate shocks across the system.

We apply four different kinds of shocks in our model: redemptions by fund investors based on climate portfolio information, a market shock on carbon-intensive assets, a market shock on assets whose issuers are most exposed to physical risk, and the realization of extreme weather events. This approach fits the bumpy adaptation of financial markets to climate challenges. In comparison, Battiston et al. [13] or Roncoroni et al. [86] are interested in longer-term impacts, i.e. over periods of more than ten years, which would reflect permanent market shifts. Although most economic climate damages will materialize in the long run, we review how short-term shocks are also likely to occur in the process while leading to socially harmful outcomes of their own. The family of network models such as this one is precisely meant to assess the impact of such shocks and their amplification. Therefore, the first three market-induced shocks used in our simulations are calibrated based on the distributions of securities' past returns. The last shock is informed by the physical risk exposures of firms. Short-term shocks are likely to revert at least partly, but their increasing occurrences could have destabilizing effects on the financial system.

We inscribe our work in the *horizon complementarities* of climate stress test, whereby short-term climate risk needs to be mitigated to best support the transition. As argued in Battiston et al. [14], financial intermediaries matter in achieving climate mitigation pathways, and this is achieved by incentivizing them in the short-term, and not solely from a long-term risk perspective. Financial soundness and stability of the financial system are a prerequisite to achieving this. Therefore, ensuring short-term robustness is of importance in the broader double materiality between climate and the nexus of finance and the real economy, i.e. how the influence between these two poles goes both ways.

Our findings suggest that the existing structure of the investment funds sector is relatively robust to climate transition shocks in terms of second-round effects but more vulnerable to the propagation of physical shocks. The former is most likely explained by the existing specialization into low-carbon industries or integration of ESG standards, which tends to segment the sector, although it does not completely preclude shocks from propagating. Regarding the latter, there is little resistance to shocks induced by market movements based on physical risk, or shocks from physical climate events themselves. This is explained by the more homogeneous exposure, so that no segment of the industry is shielded from second-round effects. This highlights the importance for the sector to monitor climate adaptation efforts in addition to decarbonization, and to reach a more holistic view of climate risk that integrates its different dimensions.

The rest of the paper is organized as follows: in section 2 we present the model used in our simulations; then, in section 3 we introduce the data used and key stylized facts; in section 4 we detail the design of the shocks applied, and discuss the results before concluding in section 5 with a policy discussion.

2 Core model

Our model is built on sets of investment funds and financial securities, represented jointly as two connected layers in figure 1. The first type of links we use are holdings by funds of marketable securities, most commonly stock shares, corporate debt and sovereign bonds. As most securities are marked-to-market, the fund portfolio values depend on their prices. The pricing mechanism (described in 2.5) relies on the common assumption that price discounts applied during fire sales cause

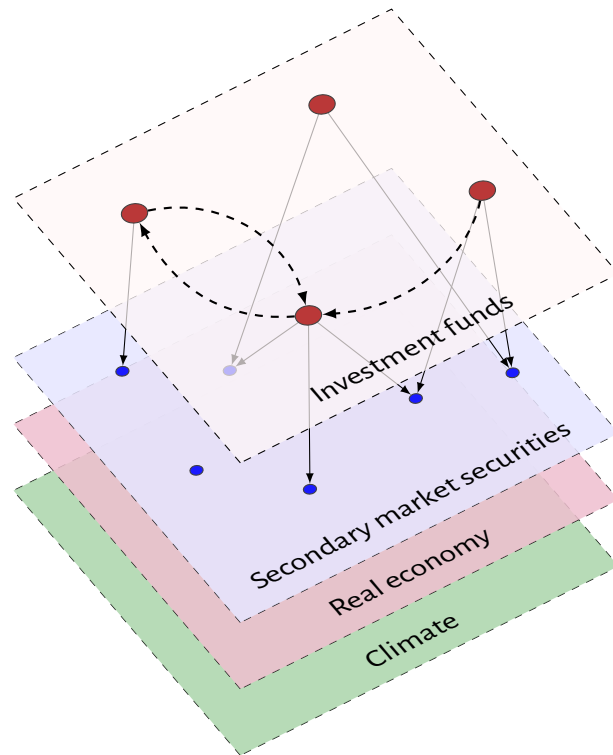


Figure 1: Stylized representation of the network agents and key links transmitting economic shocks. Dashed arrows indicate cross-holdings between funds, while solid lines indicate that a security is present in a fund's portfolio.

a medium-term depletion of asset values, allowing securities to act as intermediaries in a propagation of shocks between funds.

The second link is that of cross-holdings of shares issued by open-end funds, described in 2.2. It shares some similarity with the stock cross-holdings between banks [95]. However, the comparison is limited because bank shares are traded on the secondary market, with a price determined by demand and supply. Such is also the case of close-end funds, but open-end funds are different since their shares are not traded but can simply be bought or redeemed by investors. Moreover, their value is not determined by the market but follows the portfolio value of the issuing fund. In that, there is an automatism in the contagion that is more alike the interbank lending market, which is the focus of most of the literature on contagion risk [see for instance 10, 43]. Our model innovates in that regard relative to the existing literature, in that it provides a rigorous formalization for the shock propagation through these links.

The timeline of simulations is given in figure 2 and is designed to capture the most likely chain of events and reactions that is compatible with our narratives. The shocks applied are also reflective of the influence of all agents, i.e. not only investment funds and the secondary market, but also fund investors, both institutional and retail. In that respect, interactions between the climate and real economy layers matter as well. Market participants anticipating more stringent environmental regulations could decrease their expectations for future returns of polluting firms. Furthermore, a climate physical shock to the real economy in the form of extreme weather events could cause a number of defaults or harm economic activity, which then affects holders of securities issued by affected entities.

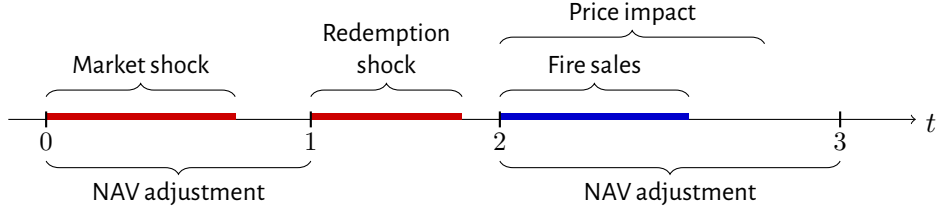


Figure 2: Overall timeline of a simulation

2.1 Mathematical notation and core model variables

For a matrix \mathbf{M} , we denote by \mathbf{M}^\top its transpose. Given an integer $n \geq 1$, let \mathbf{I}_n be the identity matrix of size $n \times n$ and $\iota_n = (1, \dots, 1)^\top \in \mathbb{R}^n$ the vector of ones of size n . By abuse of notation, for two vectors a, b in \mathbb{R}^n we write as $\frac{a}{b}$ their element-wise division when there is no ambiguity, meaning $\frac{a}{b} = (a_i/b_i)_{1 \leq i \leq n}$, and $\frac{1}{a} = (1/a_i)_{1 \leq i \leq n}$. Moreover, we denote by $\text{Diag}: \mathbb{R}^n \rightarrow \mathbb{R}^{n \times n}$ the diagonal operator, and by $\mathbf{1}_A$ the indicator function of a set A . We use bold symbols for matrices to differentiate them from vector columns and scalars in the following. Finally, given a vector or matrix a , we denote as a^+ and a^- its (element-wise) positive and negative parts respectively.³

Let n the number of investment funds in the model, and m the number of securities traded on the secondary market. We denote by $\mathbf{A} \in \mathbb{R}^{n \times m}$ the funds' portfolio matrix of tradable assets, such that for all $(i, \omega) \in \{1, \dots, n\} \times \{1, \dots, m\}$, $\mathbf{A}_{i, \omega}$ is the marked-to-market value that i holds of security ω . Thus, the total value of tradable securities of a fund i is given by $\sum_{\omega=1}^m \mathbf{A}_{i, \omega}$. The second key portfolio matrix is that of redeemable assets, i.e. how much of other funds' shares are held. It is given by matrix \mathbf{R} , such that, for $(i, j) \in \{1, \dots, n\}^2$, i holds a value $\mathbf{R}_{i, j} \geq 0$ of j 's fund share.⁴

We denote by $C \in \mathbb{R}^n$ the fund-level vector of cash holdings. Moreover, let $L \in \mathbb{R}^n$ the vector of loans from the banking sector to funds, and $B \in \mathbb{R}^n$ the vector of other assets not entering any of the previous categories. We assume that L and B remain constant, i.e. $\forall t, L(t) = L(0)$, and omit the time variable in their case. The equity of funds, or total net assets (TNA), is represented by the vector $E \in \mathbb{R}^n$. We compute it as the sum of asset holdings, from which bank loans are deducted:

$$\forall t, \quad E(t) = \mathbf{A}(t) \cdot \iota_m + \mathbf{R}(t) \cdot \iota_n + C(t) + B - L. \quad (1)$$

The net asset value (NAV), i.e. the price per share, is obtained by dividing E by the number of shares issued, and therefore in the absence of sales or redemptions evolves proportionally to E .⁵ Moreover, the prices of tradable securities are given by the vector $P \in \mathbb{R}^m$.

2.2 NAV adjustment via direct cross-holdings

We first present the mechanism that describes how the cross-holdings between funds dynamically adapt within the contagion process, as it is used at two points. Although a less commonly used channel than portfolio overlap, it appears also necessary to consider the effect of direct cross-holdings between funds as they constitute a sizeable part of their portfolios. The standard practice for open-end funds is to recompute their NAV daily and to communicate the new value when markets close.

³More precisely, in the case of a vector a we have $a_i^+ = \max(a_i, 0)$ and $a_i^- = \min(a_i, 0)$.

⁴Note that holdings of tradable securities are allowed to be negative, i.e. funds can short them, while values for cross-holdings are all non-negative. Moreover, when j is a close-end fund we have $\forall i, \mathbf{R}_{i, j} = 0$, as shares of j are counted as tradable securities.

⁵In the case of sales or redemptions, a decoupling occurs such that the NAV does not change but the TNA does.

Thus, the change in the price of marketable assets impacts the NAV of investment funds that hold them, and in turn affects the amount that their fund investors can redeem. That is true in particular when these investors are also investment funds, which makes the problem more complicated.

For instance, if a fund i holds shares of fund j and j holds shares of i , then the final value of their respective total assets has to take into account this mutual influence. One way to think about it is that, if the value of i decreases because of a shock on traded assets, then it affects the portfolio of j . Therefore, the TNA of j decreases, which in turn will impact the portfolio of i , etc. Thinking sequentially about the issue reflects this daily dynamic, whereby funds would iteratively recompute their portfolio value at fair prices and communicate it to other entities, triggering further accounting adjustments⁶ until the financial system converges to an equilibrium of share prices. But it may not do so in a finite number of rounds. In contrast, we find directly the full effect of the shock, whereby the change in market prices will establish at once new TNA. The TNA of a fund i is itself proportional across time to its NAV when the number of shares remains constant. Thus, a new price equilibrium will form.

Let t_1, t_2 be two points in time, with $t_1 < t_2$, such that marketable assets can change value or be traded by funds from t_1 to t_2 , but no fund flows are registered, i.e. there are no redemptions and no fund shares sold to investors. As some funds might default as a result, we denote by $\gamma \in \{0, 1\}^n$ the solvency vector such that $\gamma_i = 0$ if i defaults and $\gamma_i = 1$ otherwise. We will then show how fund cross-holdings will contemporaneously affect the evolution of our system between t_1 and t_2 .

Definition 1. *The network of funds is said to be regular if there exists no set $\mathbb{X} \subset \{1, \dots, n\}$ such that every fund in \mathbb{X} is fully owned by other funds in \mathbb{X} .*

This definition has the same implications as the regularity of a financial system in Eisenberg and Noe [43]. Moreover, let

$$\mathbf{r}(\gamma) := \mathbf{R}(t_1) \cdot \text{Diag}(\gamma/E(t_1)) \quad (2)$$

the matrix of relative asset holdings given defaults of γ , i.e. such that $\mathbf{r}(\gamma)_{i,j}$ corresponds to the share of j 's equity that is held by i . For tractability, we make the assumption that all funds have a positive equity at time t_1 . When $t_1 \neq 0$, this means that n has been reduced after the removal of funds defaulted in previous steps.

Proposition 1. *If the network of funds is regular, then:*

- (i) $\mathbf{I}_n - \mathbf{r}(\gamma)$ is nonsingular for all $\gamma \in \{0, 1\}^n$,
- (ii) there exists a unique internally consistent solvency vector γ^* such that $\forall i, \gamma_i^* = \mathbf{1}_{[0, \infty)}(E_i(t_2))$, with the equilibrium vector of TNAs at t_2 given by

$$E(t_2) = (\mathbf{I}_n - \mathbf{r}(\gamma^*))^{-1} \cdot (\mathbf{A}(t_2) \cdot \iota_m + C(t_2) + B - L) . \quad (3)$$

The proof of the proposition is given in appendix A.1 and stems from an established linear algebra result and a standard fixed-point analysis. As the non regularity would make little sense in practice,⁷ such cases are rare and likely to reflect data issues. Therefore, we add a step in the data

⁶Such iteration is at the core of Chrétien et al. [33], and used in Semieniuk et al. [89], where the new information of lower prices creates a shock to portfolios, based solely on financial entities posting new information about their value.

⁷Consider that it means the total assets of these funds, except fund shares within the group, equals its total external debt. This is unlikely, first because funds' profits are primarily meant to go to shareholders and not (only) to creditors, and second because most investment funds have a low leverage, often by law.

preparation process to remove funds that belong to groups causing irregularity. Moreover, consequently to definition 1, when starting from a network that is regular, any subnetwork with some funds removed will also be regular. Therefore, when the initial network is regular, the ones obtained at later rounds after removal of defaulted funds do not have to be checked.

In a larger financial system, if there is no additional cycle,⁸ the assets of other financial institutions can be updated simply by applying the price changes $\frac{P(t_2)}{P(t_1)}$ and $\frac{E(t_2)}{E(t_1)}$ on their tradable and redeemable holdings respectively (the latter being due to a total number of shares assumed constant during that step). For the system of funds we apply the equation

$$\mathbf{R}(t_2) = \mathbf{R}(t_1) \cdot \text{Diag} (E(t_2)^+ / E(t_1)) . \quad (4)$$

In our framework, we use this mechanism twice. But that needs not be the case and this choice is essentially based on a narrative where different actions happening within the system take a certain time to materialize. For the NAV adjustment, a daily update could in practice deliver the biggest part of the impact in a short time. Only in a system with long chains and cycles of cross-holdings would we expect that the impact after a few days is still significant. To that extent, it seems reasonable to assume that the NAV adjustment happens several times, in parallel to every event that would trigger it.

2.3 Market shock

In the simulation, funds are exposed to a dual stress materialization: a market shock and a redemption shock. First, the market shock applies to assets present in the funds' portfolio as their market value changes. A typical example would be common shares of brown firms losing value at the introduction of more stringent environmental regulations, or a firm defaulting because it lost physical capital and income following an extreme weather event. The shock is represented by a vector $\Lambda \in [-1, \infty)^m$, such that $\forall \omega, P_\omega(1)/P_\omega(0) = 1 + \Lambda_\omega$. It impacts the funds' portfolios of tradable assets, with $\mathbf{A}_{i,\omega}(1) = \mathbf{A}_{i,\omega}(0) \times (1 + \Lambda_\omega)$ for all (i, ω) .

Moreover, $C(1) = C(0)$ because the market shock had no effect on cash. Given $\mathbf{A}(1)$ and $C(1)$ we can then compute $E(1)$ and $\mathbf{R}(1)$ using equations (3) and (4) respectively. Following this step, funds with negative or null equity are removed from the system and considered in default.

2.4 Redemption shock

The second shock applied is that of redemptions, which creates a liquidity stress for some funds, although it can be positive net flows for others. The redemption shock comes from investors external to the system of funds. A number of events can push them into moving significant quantities of their assets in a short period of time, resulting in large inflows or outflows for investment funds [58]. It is represented by a vector $\Psi \in (-1, \infty)^n$ of net flows, which is the ratio of shares sold relative to the previous total. That means Ψ_i is negative if net redemptions occur for fund i , and positive in the case of net sales.⁹ We suppose that redemptions are immediately paid, the shares purchased immediately issued, and the consequences are dealt with in the next step. Thus, we account for it as impacting

⁸The presence of a feedback loop with other agents, contemporaneous to the one taking place between funds, could invalidate equation (3) in a larger financial system.

⁹The assumption $\Psi_i > -1$ ensures that there is no complete run from investors, and therefore no default consequent to this step.

the cash reserves of funds:

$$\forall i \in \{1, \dots, n\}, \quad C_i(2) = C_i(1) + \Psi_i \times \left(E_i(1) - \sum_j \mathbf{R}_{j,i}(1) \right), \quad (5)$$

where $E_i - \sum_j \mathbf{R}_{j,i}$ corresponds to how much of i 's equity is held by external investors. Then, the new TNA vector is given as $E(2) = E(1) + C(2) - C(1)$. Applying the NAV adjustment mechanism would not be useful here, because fund flows do not affect the NAV *per se*, so $\mathbf{R}(2) = \mathbf{R}(1)$. Lastly, $P(2) = P(1)$ and $\mathbf{A}(2) = \mathbf{A}(1)$ as redemptions have no impact on asset prices. We apply this step after the market shock, which corresponds to a narrative where investors react to changes in the market and do not anticipate them, leaving open the possibility to calibrate the redemption shock based on the market shock, through a flow-performance relationship. We use the following piecewise linear model:

$$\forall i \in \{1, \dots, n\}, \quad \Psi_i = \mathbf{q}_i + \mathbf{r}_i \left(\frac{\Delta E_i(1)}{E_i(0)} \right)^+ + \mathbf{s}_i \left(\frac{\Delta E_i(1)}{E_i(0)} \right)^-, \quad (6)$$

meaning that investors can have a sensitivity to positive returns that is different from that to negative returns. This is used for open-end funds only, and we set $\mathbf{r}_i = \mathbf{s}_i = 0$ when i is a closed-end fund. Such a mechanism has been used in related models, such as Mirza et al. [73], but is generally fully linear, or operational on the negative domain only. Thus, our model is the first to fully embed some convexity, a prominent stylized feature observed in the literature.

Note that from a macro-prudential policy point of view, the underlying narrative is different in the case of climate shocks than with a broader economic shock. In the latter, tools such as redemption suspensions usually appear as a valid solution to mitigate spillover effects.¹⁰ However, this solution has downsides, such as a reputational risk. This risk relates to the behaviour of investors vis-à-vis certain funds and might be limited in the case of a recession. When the shock is more differentiated between investment funds, with only some being hardly hit, there could be a higher toll on reputation from taking measures that restrict investors. Thus, there is a shift in the incentives of funds when it comes to using these tools, such that part of the prudential toolbox loses in relevance.

2.5 Fire sales and price impact propagation via portfolio overlap

A large literature exists on fire sales and contagion through portfolio overlap. It has also been identified by the Financial Stability Board as an amplification risk in case of climate shocks [48]. We build here on existing techniques, with the advantage compared to some previous works of using asset-level information. This avoids the network distortion and overestimation of price impact that can occur when assets are aggregated.

First, in order to meet redemptions from investors, funds will reduce some of their positions, prompting fire sales. The use of cash buffers¹¹ can change significantly the magnitude of the following step. Similarly, we know from bank network models that the extent to which banks are willing to deplete their liquidity coverage ratio has a key influence on subsequent fire sales [35, 53]. We make

¹⁰Grill et al. [51] relate how this was used in the face of the market shock induced by the COVID-19 pandemic. They observe a stronger usage by more vulnerable funds, i.e. leveraged, illiquid, or with little cash holdings.

¹¹Although we depart from it, Zeng [103] provides an important model explaining why funds would try to replenish their cash buffers in the period following redemptions. Chernenko and Sunderam [32] and Huang [56] provide further background regarding the cash management of funds.

the hypothesis of fixed cash targets, which can be calibrated at the fund level.

Based on cash targets, we calculate how much each fund wishes to sell or purchase of each asset, extending on the mechanism of Sydow et al. [96], with funds anticipating the price impact of transactions given below in equations (7) and (8). Given $\mathbf{S} \in \mathbb{R}^{n \times m}$ the matrix of final sales at initial prices, the volumes sold by assets are given by vector $s = \mathbf{S}^\top \cdot t_n \in \mathbb{R}^m$. That is, s_ω is the net value of ω , at initial market prices, that is sold by investment funds for each security. We model the price impact of fire sales based on the exponential specification in line with Cifuentes et al. [34] and Fukker et al. [49], but allowing for a symmetric behaviour in case of purchases:¹²

$$\frac{P_\omega(3)}{P_\omega(2)} = 1 + \mathbf{b}_\omega \times \left[\exp\left(\frac{-s_\omega^+ \cdot \mathfrak{d}_\omega}{K_\omega(2) \cdot \mathbf{b}_\omega}\right) - \exp\left(\frac{s_\omega^- \cdot \mathfrak{d}_\omega}{K_\omega(2) \cdot \mathbf{b}_\omega}\right) \right] \quad (7)$$

where \mathfrak{d}_ω is the price impact illiquidity coefficient of ω , \mathbf{b}_ω is the price impact boundary, and K_ω is its total market value, which corresponds to the total market capitalization for stocks or the total amount outstanding for bonds. This price impact function achieves a concavity of the price drop on volume, which is a key feature observed empirically [97].

As tradable assets are marked-to-market, the new matrix of external holdings and new cash holdings are given respectively by

$$\mathbf{A}(3) = [\mathbf{A}(2) - \mathbf{S}] \cdot \text{Diag}\left(\frac{P(3)}{P(2)}\right), \quad \text{and} \quad C(3) = C(2) + \mathbf{S} \cdot \frac{P(3)}{P(2)}. \quad (8)$$

Moreover, we are able to compute $E(3)$ and $\mathbf{R}(3)$ using equations (3) and (4) respectively.

As noted in [37, 92], fire sales would materialize when the number of buyers is small compared to sellers, which is more likely to happen when the initial pool of investors for one stock is small. To that regard, fire sales are important to climate stress testing in so far as climate shocks are likely to be localized geographically or focused on some policy-relevant sectors (see section 3.2). Because funds are often specialized along the same dimensions, a limited number of them would be natural buyers of certain securities. As a consequence, climate shocks are likely to lead to sensible fire sales discounts, because many similarly specialized counterparts, who could have bought the stocks in normal times, will be experiencing distress as well.¹³

3 Data and measures of exposure to risk

We employ data from a range of different sources. Part of it is investment funds granular data, similar to [96]. The remainder consists of the same climate-related primary data sets as [3].

3.1 Investment fund data

Our primary source of data for investment funds is the Lipper Global Data Feed provided by Refinitiv. The dataset available covers complete holdings of open-end and closed-end investment funds. Holdings data is available monthly and is well populated for the period from mid-2018 to mid-2020.

¹²It is symmetric compared to most of the related literature that does not consider purchases, because they have a shock that is negative across all assets [see e.g. 26], and thus are purely asymmetric. Note that we can make the reaction easily asymmetric by defining two coefficients \mathfrak{d}_ω and \mathfrak{h}_ω instead of a single \mathfrak{d}_ω used on both sides.

¹³On the contrary, trading against constrained funds has been identified as a profitable strategy [39]. A configuration where funds in our sample benefit from this effect is possible, e.g. if they are sufficiently shielded from negative shocks but have some brown positions that they can expand by taking advantage of browner funds' distress.

We choose to use values from December 2019 as the default for our simulations, based on data availability, recency, and to avoid periods at the core of the market downturn induced by COVID-19. We adopt the static balance-sheet hypothesis, which subsumes that, until the moment the shock is applied, the balance sheet of institutions remains identical to a past balance sheet known from the data. Thus, as the application relies on this hypothesis, its informative value is only significant in the time frame where the static balance-sheet hypothesis appears as a valid approximation. The use of this hypothesis is common in climate stress tests [e.g. 3, 11, 70, 101] and it appears reasonable here compared to existing longer-term climate stress tests. Furthermore, we run simulations for other months as well.¹⁴ The use of data from different points in time over the past years provides additional security with regard to the static balance-sheet hypothesis, which now comes down to having future medium-term portfolios close to the range of those recently observed.

At the time chosen, the number of funds that are active and hold securities¹⁵ in our sample is 23,216. They issue a total of 68,006 distinct fund share classes. The number of end-of-month holdings of external assets (other than cash or inter-fund holdings) is over 3.3 million, and the number of inter-fund holdings is above 41,000. Additional statistics on the funds are provided in Appendix B.

As analysed in Cera et al. [31], nonbanks present a significant connection through overlapping portfolios within-sector as well as with the banking sector. This is a key motivation for the use of the dynamics presented here in the context of a system-wide stress test. Moreover – when looking at the funds specifically – we can decompose in two the contagion risk *a priori* within the sector: through overlapping portfolios and through direct holdings. To measure the contagion risk from overlapping portfolios we use the cosine measure of portfolio similarity, and similarly, we can define the similarity of i 's portfolio to that of the sector as a whole, denoted $S_C(i)$. As these measures are standard, details are given in appendix A.3.

When it comes to the risk coming from cross-holdings, the dynamics are not symmetric, so two measures would be needed. We focus here on the one that quantifies the risk transmission to others from the dynamics of 2.2, i.e. how much the change in the NAV of i will affect counterparts within the fund sector. It is given by

$$\zeta_i = \frac{1}{E_i} \sum_{j \neq i} \mathbf{R}_{j,i}, \quad (9)$$

such that $\zeta_i = 1$ when i is fully owned by other funds and propagates the entirety of its NAV shock within the system of funds. We combine in figure 3 the two measures $S_C(i)$ and ζ_i . Our data suggest that most funds have a relatively low contagion profile, as the bottom-left corner is very densely populated, which is confirmed by the marginal distributions. Moreover, we observe a few big funds that present a high risk on both dimensions, but some appear risky on one of the two aspects, especially portfolio overlap.

3.2 Carbon intensity data

Our first source of data pertaining to the environment is a dataset of firm-level carbon emissions created by Urgentem. It provides data on carbon emissions under scopes 1, 2 and 3. For this exercise,

¹⁴Comprehensive results for other months are generally not presented here but are available upon request.

¹⁵More precisely, the filtration applied to the data to select funds has four components: funds need to have at least some tradable holdings (standard stocks or debt securities) or redeemable holdings (the fund shares issued by other funds included), they should have positive initial equity, this equity cannot be smaller than the total market value of the shares they issued that are reported in the portfolios of other funds, and finally, they must not belong to a group that would cause regularity to be breached.

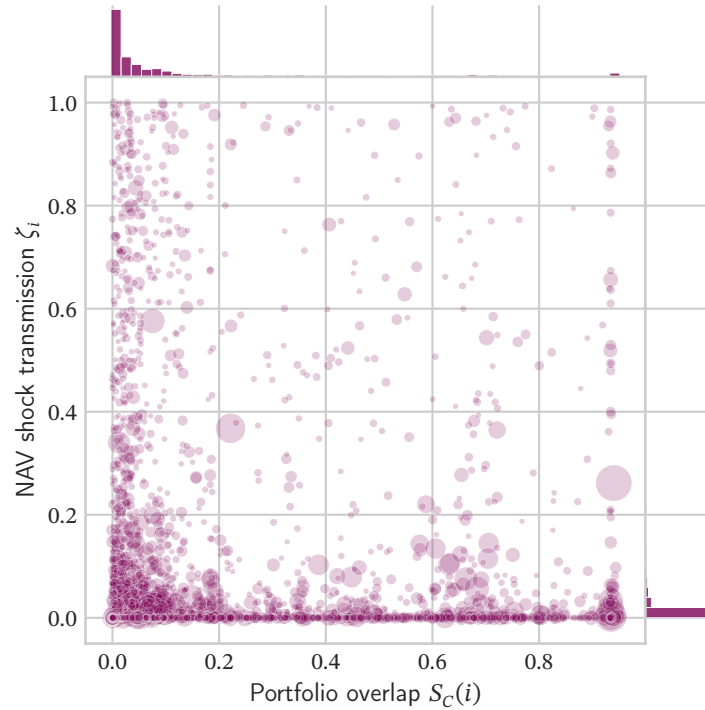


Figure 3: Risk profiles of funds from both portfolio overlaps and cross-holdings. Scatter plot with marginal distributions of funds along both risk dimensions, with the x-axis corresponding to $S_C(i)$ and the y-axis displaying ζ_i , as defined in equations (15) and (9) respectively. For visualization purposes, only the biggest funds are represented, i.e. the top 20% by equity whose assets include either tradable or redeemable holdings. The area of each dot is proportional to the corresponding fund's equity. The marginal distributions are unweighted, i.e. based on the number of funds and not on their sizes. Sources: Refinitiv and authors' calculations.

we use the inferred average carbon intensity on scopes 1 and 2, which is measured in tons of CO₂-equivalent per million dollars of revenue. The data set used is from October 2020 and covers 46,447 firms. For each of them, observations can be reported for different years. Therefore, we use for every company the most recent reporting available.

We will assume that these scores are indicative of exposure to transition risk. Indeed, highly carbonated supply chains are more likely to become stranded assets or generally less profitable as new climate policies increase the environmental liability of polluting firms.¹⁶ There are some limitations to proxying transition risk as GHG emission intensities, as it has not been a clear determinant of prices in the past [22]. Nonetheless, it appears as a central factor of transition risk for real economy firms, e.g. in the case of a carbon tax. Moreover, in the context of our exercise, part of the transition risk comes from the market reacting to new policy shocks based on better information than before, for instance, more robust measures of carbon intensity in the value chain instead of sector information only. Therefore, what matters is more the information that the market would rely upon rather than the actual long-term determinants of stranded assets and loss of profitability from transition policies. Industry sectors themselves are strong indicators of emission intensities, as we can see from figure 14a, presented in appendix B. Lesser but still significant variations can be observed between countries when aggregating assets at the national level.

¹⁶It includes direct carbon pricing, heftier fines in case of breaches of environmental regulations, costlier risk management, etc.

The main limitation faced is that of funds that only have a small portion of their portfolio covered by Urgentem data. Nevertheless, for the purpose of our stress test, we proxy part of the missing holdings using country and sector information.¹⁷ Then, let \mathbb{U} denote the subset of securities with carbon intensity data, and $(g_\omega) \in \mathbb{R}_+^{\mathbb{U}}$ the carbon intensities of assets. Based on this we define a fund-level carbon intensity for portfolios:

$$\forall i \in \{1, \dots, n\}, \quad g_i^\dagger = \frac{\sum_{\omega \in \mathbb{U}} \mathbf{A}_{i,\omega} \times g_\omega}{\sum_{\omega \in \mathbb{U}} \mathbf{A}_{i,\omega}}. \quad (10)$$

These values have the advantage of being directly comparable to firm-level carbon intensities. The methodology is standard in the literature. Note that we do not reward funds that are good at screening for green firms, except for the “natural” advantage of firm-level scores. For instance, suppose that i and j invest in the same sector, but i is better at picking green firms while j is uninformed about greenness. Thus, suppose that i 's portfolio comprises firms that pollute on average 30% less than those of j . Then, g_i^\dagger will also be 30% smaller than g_j^\dagger , but it would remain high compared to another uninformed fund k investing in a sector that structurally pollutes much less.

Note that a variety of data providers currently exist, which provide the market with similar information. As discrepancies can exist between them, and carbon accounting methods are complex and imperfect, we do not claim that the measure used in this paper is superior to that developed elsewhere.¹⁸ This uncertainty is also a limitation as to how precisely markets can currently be stirred to mitigate climate change. However, as we aim to provide a stylized example of how network externalities materialize in reaction to climate shocks, we can use this data assuming that it is good enough to be in line with information available at the time of future climate shocks.

From this construction, we classify funds based on how green their portfolios are. In figure 4 we compare funds when grouped into different buckets (deciles) based on their carbon intensity. Descriptive statistics related to this grouping are presented in the appendix, figure 15a. These figures reflect the expected strength of shock propagation between different groups, where funds within one group are expected to suffer similar initial losses from transition risk. Therefore, it matters if for example an amplification of a transition shock happens mostly between brown funds or if it could propagate to the broader network.¹⁹

Figure 4a looks at the portfolio overlap channel, i.e. building on inter-funds common holdings. Its analysis indicates that an amplification within the browner half of funds is indeed plausible. This is consistent with Amzallag [5], which finds that few funds invest in the same green firms, while brown firms have numerous investment funds as shareholders. This is partly confirmed here, with the top decile of green funds having very little overlap with the rest.²⁰ However, the following deciles present a stronger overlap with the rest, and the tenth decile also seems to present little overlap with

¹⁷Given an asset ω for which we know the country and economic sector of the issuer. If the set of firms in that country-sector intersection is larger than 20, we average their carbon intensities and use it as a proxy for ω . Otherwise, we use the average of the whole sector across countries. Sector information is taken from NACE codes, at the two-digit level.

¹⁸See for instance Janssen et al. [63] for the bias of carbon intensity to shifts in exchange rates.

¹⁹Recent work at ESMA has already emphasized this interconnection between brown funds and its implication in case of shocks [5]. Following the framework of Cont and Wagalath [36], one could suspect that even if green and brown assets were fundamentally uncorrelated or negatively correlated, the distressed selling by funds would induce a positive excess correlation between them.

²⁰Nonetheless, one could explain this discrepancy by the lack of maturity of green financing, and we cannot exclude that sustained flows to green funds eventually modify the sub-sector topology. Thus, the appearance of hubs among green securities is a plausible future stability threat.

other groups. Overall, common holdings do not seem likely to propagate shocks from the brownest tier of funds to the greenest one, but the channel as a whole matters in the analysis.

In figure 4b, we see the nominal cross-holdings between the different fund families. Firstly, we see that non-classified funds are the largest holders in general, in part because the group is much larger, and because it contains most funds of funds. Secondly, although no overall pattern emerges, it appears that funds from the first and tenth deciles are the ones most held by others. In that regard, Ammann et al. [4] find past shifts in flows to be consistent with a reallocation by investors within fund families from least to most sustainable funds, and they suggest that sustainable funds are more likely to be actively marketed within a fund family. Meanwhile, the holdings of fund shares are not taken into account in sustainability indices, such as that by Morningstar’s Portfolio Carbon Risk Score, which is then used to identify “Low Carbon” funds [54]. In line with this, the appeal of high-carbon funds would be consistent with a form of greenwashing where part of the flows to more popular sustainable funds would be redirected to brown funds, with no implied penalty in terms of their sustainability ratings.

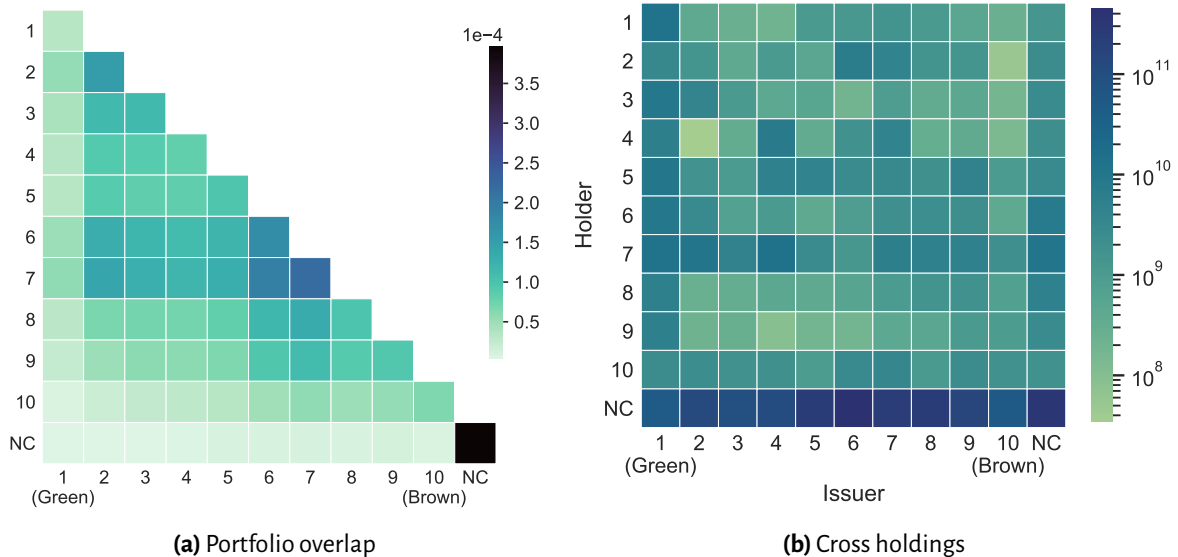


Figure 4: Connections between subsets of funds based on their carbon intensity. Investment funds are pooled into deciles based on their carbon intensity. Those with less than 50% of their portfolio scored are placed in the NC group. Left panel: the portfolio overlaps are given by cosine similarities (see equation (14) in Appendix B). The value between two deciles x and y is given by the mean overlap between funds in decile x and those in decile y (excluding the overlaps of funds with themselves when $x = y$). Right panel: the cross-holdings are given by aggregated nominal amounts in euro, i.e. how much funds in one group own of funds in another group. Sources: Urgentem, Refinitiv and authors’ calculations.

3.3 Physical risk exposure data

The second important input, also at the firm level, is a dataset created at the ECB from physical risk information provided by Four Twenty Seven. Based on precise locational data and the sector of activity, risk exposure scores are allocated to firms for the different catastrophe types: floods, heat stress, hurricanes and typhoons, sea level rise, water stress, and wildfires. Each score is given as an integer between 0 (least exposed) and 100 (most exposed). In figure 14b, in the appendix, are given

the average risk exposure of firms for each country. In particular, islands such as the Virgin Islands or Japan occupy the top places due to the high idiosyncratic risk induced by their topology. A total of 117 countries have firms present in the dataset used.

Our standard indicator of physical risk is an average of the scores on the above-mentioned exposures. Similarly to the Urgentem data, we denote by \mathbb{V} the subset of securities to which we attach a physical risk exposure, and $(h_\omega) \in [0, 100]^\mathbb{V}$ the mapping from assets to average physical risk exposure. Thus, the fund level exposure to physical risk is given as

$$\forall i \in \{1, \dots, n\}, \quad h_i^\dagger = \frac{\sum_{\omega \in \mathbb{V}} \mathbf{A}_{i,\omega} \times h_\omega}{\sum_{\omega \in \mathbb{V}} \mathbf{A}_{i,\omega}}. \quad (11)$$

The dataset provides exposures for a total of 4,3 million firms, by their Orbis identifiers. A total of 128,581 can be mapped to LEI codes. As many assets are not directly covered, we use location-based proxies,²¹ which adds roughly almost five times the original number. A decomposition into deciles based on the fund-level physical risk measure is also used for the related simulations, with corresponding statistics given in table 15b. Finally, note that similarly to the case of carbon intensity, important discrepancies exist between different data providers for physical risk exposure [52].

3.4 Data matching and fund scores

A key challenge of this exercise is to bring together the data used consistently. In particular, the carbon intensity and physical risk measures introduced rely on attaching climate-relevant information as well as sector, location or financial information to the set of asset holdings. We rely primarily on the ISIN codes of securities, as well as the Legal Entity Identifiers (LEI) of firms. The main resource used is the Centralised Securities Database (CSDB) [25], maintained by the European System of Central Banks. Table 1 details the coverage of this matching for carbon intensity data across different categories of assets. Importantly, we may not want to interpret all matched climate scores equally. For instance, their use in the case of sovereign bonds has a less clear meaning, while they constitute an important part of the sector's holdings. For that category in particular, the relative lack of exposure data relative to the rest means that they will be less shocked. It appears reasonable for sovereign bonds to be more shielded from short-term shocks, as the transmission channels from climate risk to governments generally consist of longer-term dynamics.²² Additional information on the total market valuation of firms is obtained through the Orbis database by Bureau van Dijk. Firms with market valuation data covering at least three years are kept, and the values for missing months are interpolated where needed.

The key value added and novelty of this is that we can decompose climate risk along its transition and physical dimensions, based on our different indicators. Although the matching is not complete, this can be first visualized at the firm level. We show in figure 5 the joint distribution of risk obtained from these two rating methods, on the universe of firms with complete information. The firms included are all those with information available, and not only the ones issuing on the market. The next step is observing this at the fund level. As funds have portfolios that are at least somewhat diversified we observed fewer outliers than when looking at firms directly. Crucially, we can notice

²¹Given an asset ω that cannot be mapped to the Four Twenty Seven dataset, we may know its country and postcode from the Register of Institutions and Affiliates Data (RIAD) database. In that case, we proxy its exposure as the average from firms sharing the same postcode, with the condition that there exist at least five of them.

²²See Battiston et al. [11] for a stress test of these securities.

	Number	Market weight (% by value)	With carbon intensity (%)	With physical risk (%)
Agencies	29,944	3.01	96.34	35.82
Convertible Bond	12,695	0.26	99.96	31.48
Corporate Bond	892,122	10.70	99.39	46.32
Equity shares	1,947,412	69.39	99.95	33.96
Fixed Income	23,765	0.33	82.95	29.65
Mortgage-Backed Security	188,457	2.66	92.73	27.32
Municipal Bond	56,950	0.83	0.49	2.39
Preferred Stock	18,059	0.42	99.56	51.13
Sovereign Bond	154,317	11.14	0.54	20.53
Supranational	9,851	0.15	95.72	1.30
Other	41,978	1.12	87.13	17.11
Total	3,375,550	100.00	92.85	35.48

Table 1: Fund holdings covered by carbon emission and physical risk data for end-2019.

“Number” corresponds to the total count of securities of the category within the set of holdings, with “Market weight” indicating the weight of each category by market value. The last two columns indicate the ratios covered by scores from the Urgentem and Four Twenty Seven datasets respectively, within each category (by the number of securities and not weighted by market values).

Source: Refinitiv, Urgentem, Four Twenty Seven and authors’ calculations.

that the point of higher concentration for funds is closer to the upper-right corner. This suggests that investment funds have a bias towards relatively riskier firms, both from the transition and physical perspective.

More precisely, from an analysis of transition risk alone, we find that in 2019 the carbon intensity of the funds’ assets was on average in excess by 6.9% compared to our unweighted sample of firms with data (excluding those proxied). This dimension corresponds to the x -axis in the left-hand side of figure 5. In this case, the bias of funds is lower than that of the market in general (based on the total market capitalization of firms), which is in excess of 14.8% on average over the same period.²³ This means that the funds included in our sample correct already for part of market excesses when defining their portfolios. However, that is insufficient to reach an actually “virtuous” level of carbon intensity, which would have to be below our general benchmark. A visualization for the related time series is available in figure 6a. We observe in particular that the carbon intensity of both markets and investment funds has been decreasing on average over the last three years. This is in line with findings from IMF [60], showing a carbon intensity with the same metric but different data. The authors further analyse that the decrease is driven by funds’ portfolio allocation, and not by changes in the firm’s score. In our case, we use here fixed firm scores, corresponding to the latest known data point, hence a decrease fully attributable to allocation and prices.

When looking at physical risk, the excess exposure of funds relative to our unweighted sample of firms is 34.2% in 2019 on average, compared to a general market excess of 26.0%. This means that a bias toward riskier assets is built up on two levels. First, firms with higher physical risk exposures tend to issue more on the market. Second, investment funds tend to invest more heavily in riskier firms, even relative to securities available. The latter step is presumably not carried out on purpose but as an externality of investment strategies that present a positive correlation with physical risk. For instance, the lack of investment in adaptation might be rewarded, as it would be financially

²³The market bias toward more carbon-intensive firms is already known in the literature and affects other institutions such as central banks [71].

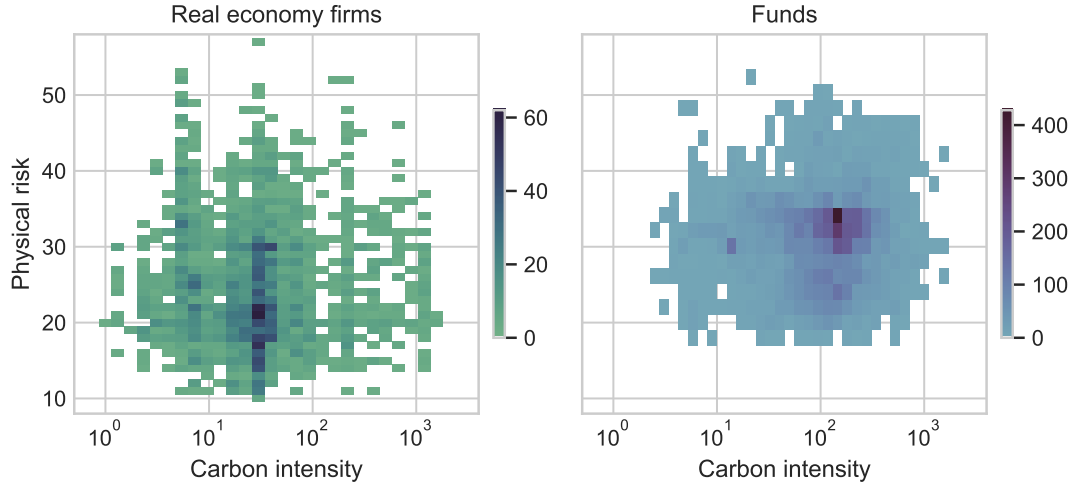


Figure 5: Joint risk distributions for firms of our sample and investment funds.

Both plots are given as bi-dimensional histograms, with the colour scale indicative of the number of entities of each tile. For both panels, the x-axis corresponds to the carbon intensity measure, in log scale, while the y-axis is indicative of the physical risk exposure. Left panel: data for real economy firms included in our sample. The joint representation is obtained after matching both types of data on the LEI codes. Right panel: data at the fund level after taking weighted averages of portfolios.

Source: Refinitiv, Urgentem, Four Twenty Seven and author's calculations.

advantageous in the very short term. The related time series is represented in figure 6b. To the contrary of carbon intensity, both exposures to physical risk have been slightly increasing (which reflects portfolio choices as the physical risk values of securities are fixed here).

Overall, there seems to be a potential for funds to pivot their portfolios towards firms that are better prepared for climate change impacts, and to a lesser extent less polluting. Furthermore, even a relatively safe portfolio does not prevent the effect of contagion coming from more exposed funds in the short term, and over a longer horizon, this exposure is likely to materialize as significant losses if markets and portfolios do not evolve sufficiently.

4 Results

Given a system of investment funds built from our data, we estimate its reaction to shocks following a propagation mechanism as described in section 2. The shocks are defined in this framework, i.e. as an initial change in prices Λ and initial fund flows Ψ .

First, in section 4.1 we benchmark the system of funds against uniform shocks, such as used in a number of other papers. Second, we design several plausible shocks based on climate data features that translate into risk for portfolio exposures. This allows a finer event analysis than exercises that rely on a pure redemption shock, often not using granular fund features [44].

4.1 Sensitivity analysis from uniform shocks

One way to test our model and simulation framework is to observe its response when faced with uniform shocks from the market. That means we apply a series of shocks $\lambda \in [0, 0.4]$ such that $\mathbf{A}(1) = (1 - \lambda) \cdot \mathbf{A}(0)$. Coarse shocks such as a uniform change in the yields of bonds are standard

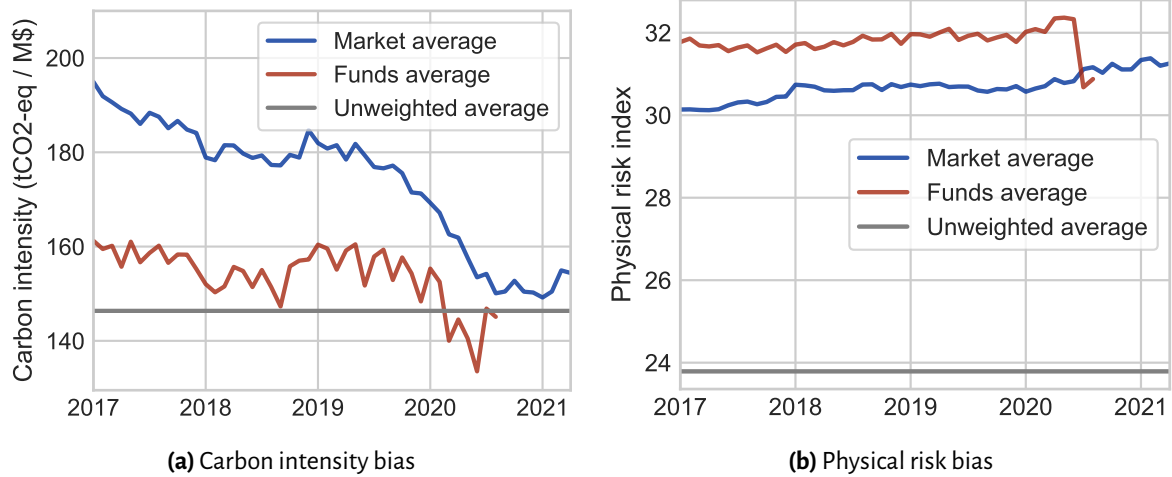


Figure 6: Quantification of the bias of financial markets and investment funds for riskier assets on the transition risk and physical risk dimensions.

The unweighted average is taken as a simple mean of the carbon intensity or physical risk index respectively. These two variables are the ones defined in section 3. The value is constant as we generally do not have full times series available for these data, and we use the last value known for the sub-sample of firms where different points in time are available. The “Funds average” value is obtained as a weighted average of the climate variable, where the weights are given by the proportion of securities in the aggregated holdings of all funds in our sample. Likewise, the “Market average” is obtained as a weighted average of the respective climate variable where weights used are the total market valuations of assets.

Source: Bureau van Dijk’s Orbis, Urgentem, 427, Refinitiv and authors’ computations.

in the stress testing literature where the focus is on the model and not on the scenario.²⁴ Using it allows us to compare more easily our results. This is done in combination with redemption reactions based on a linear flow-performance relationship. Different values for the flow-performance driving coefficients are tested. Results are decomposed into the following components:

- a) direct gains and losses from the initial market shock;
- b) gains and losses from the first round NAV adjustment on cross-holdings;
- c) outflows from the performance-based redemption shock;
- d) gains and losses from the price impact;
- e) gains and losses from the second round NAV adjustment on cross-holdings.

We reference as indirect gains the components b), d), and e). For each of these components we take the sum over all funds covered in our analysis. The output using our reference month of December 2019 is given in figure 7. Note that the first plot is linear because it is equal to $-\lambda \sum_i \sum_\omega \mathbf{A}_{i,\omega}$, and the second one as well, since based on equation (3), the overall reaction of the equity to the initial market shock is linear as long as the set of defaulted funds induced by γ^* does not change.

Variations of the flow-performance function are tested here with a linear specification $\forall i, \tau_i = \varsigma_i = \hat{\tau}$, and $\eta = 0$. The absence of the convexity feature matters little here as we only consider negative shocks. We observe that the price impact has a small positive effect in the absence of a flow-performance reaction. Indeed, this corresponds to a case where funds with mostly long holdings see the value of their portfolio decrease, while the cash and equivalent maintains the same value. Thus, cash rises in proportion of total holdings, and as no liquidity shock follows, funds can buy

²⁴Some scenarios such as the ones used by the EBA also feature shocks on securities with little granularity, i.e. defined at the country level.

securities to maintain the same cash ratio. Furthermore, note that the negative effect of the price impact disappears for large negative shocks in our framework in the case of an important flow-performance relationship.²⁵ This is because the negative price impact effects are limited by the ratio of external investors that can redeem, and the share of tradable security over the whole portfolio that can be sold or affected by the trades of others. Thus, the positive effect takes over after some point due to the funds with short positions and those with a small external investor base where the flow-performance effect is small.

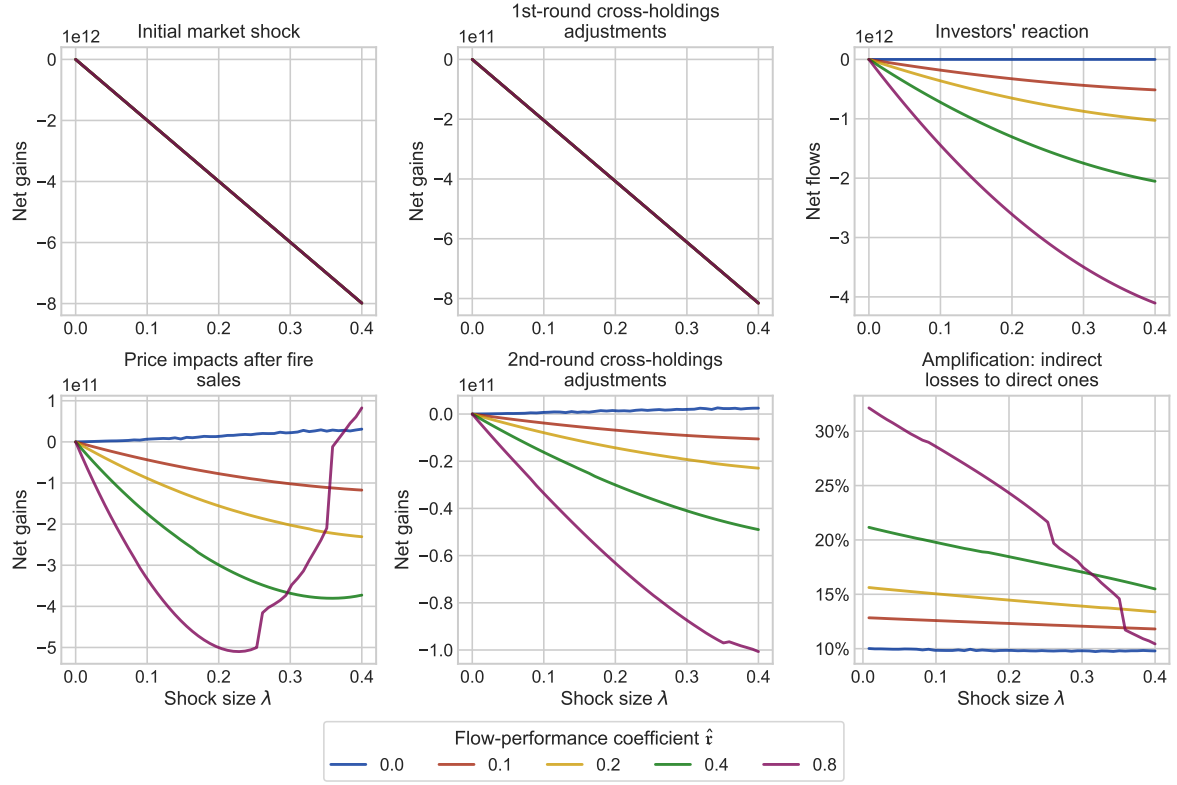


Figure 7: Decomposition of the effects of a uniform shock.

The first five charts correspond to components a to e described in 4.1. Their x-axis denotes the shock λ that is uniformly applied to all prices, and the y-axis is the amount in euro. The last chart represents the amplification of the initial shock, taken as the ratio of all indirect gains (components b , d and e) to the initial shock (a).

Source: authors' calculations.

It comes that the average amplification as defined above also provides a benchmark to compare the effect of other shocks on the period between times 0 and 1. Yet, this does not provide for a comparison over the whole simulation. To this end, we will use uniform shocks as the benchmark for simulations with heterogeneous market shocks. Given a general price shock Λ as used in section 2.3, define the direct gains function $g_1 : \Lambda \mapsto \iota_n^\top \cdot \mathbf{A} \cdot \Lambda$. Then, the uniform shock that results in the same direct gains as Λ is given by

$$u(\Lambda) := \left(\frac{g_1(\Lambda)}{\iota_n^\top \cdot \mathbf{A} \cdot \iota_m} \right) \iota_m, \quad (12)$$

i.e. such as $g_1(\Lambda) = g_1(u(\Lambda))$. Then, we use this shock as a base to qualify the indirect gains

²⁵The largest flow-performance coefficient of 0.8 that is used here is larger than our calibrated coefficients for negative returns given in 4.3, but smaller than the ones used for positive returns.

$g_2(\Lambda)$ that follow market shock Λ , which is given by the sum of components b , d and e above, and $IS(\Lambda) := g_2(\Lambda)/g_2(u(\Lambda))$ the indirect severity indicator. We will then say that Λ exhibits severe indirect effects if $IS(\Lambda) > 1$, and mild indirect effects if $IS(\Lambda) < 1$.

Moreover, this exercise proves that second-round effects exhibit a strong sensitivity to the flow-performance parameter. While the magnitude of the reaction is fading in the last steps, it remains economically sizeable. Moreover, in the context of a larger stress test, with all financial agents accounted for, losses would be larger as they account for the funds' total reduction in equity and the effect of price changes on all securities present in the market.

4.2 Transition shock with score-based redemptions only

In a first stage we study the effect of a shock that affects funds through net flows only, i.e. with no initial market shock. This corresponds to a narrative of a policy shock designed specifically to benefit green investment intermediaries, e.g. an extended official labelling of funds based on carbon intensity, or a change by market data providers in the information on carbon intensity that is given to investors. This could also reflect more general policies such that the reaction from fund investors trumps the effect on security prices.

In figure 8 we show that a climate policy announcement such as the Paris Agreement can be correlated to unusual flows, with in particular an effect on funds that classify as *socially responsible investment* (SRI) or *environmental, social, and governance* (ESG) that experienced significantly higher flows than their average. The effect observed is in line with Monasterolo and De Angelis [75], which finds that the Paris Agreement has made green finance more appealing without penalizing significantly carbon-intensive assets. Moreover, Ceccarelli et al. [29] and Hartzmark and Sussman [55] show that improved information on sustainability and carbon-related risk also has a potential to affect flows, favouring most sustainable funds at the expense of the least ones. Thus, existing evidence points to the fact that investors react to the available information and internalize the expected consequences from transition policies.

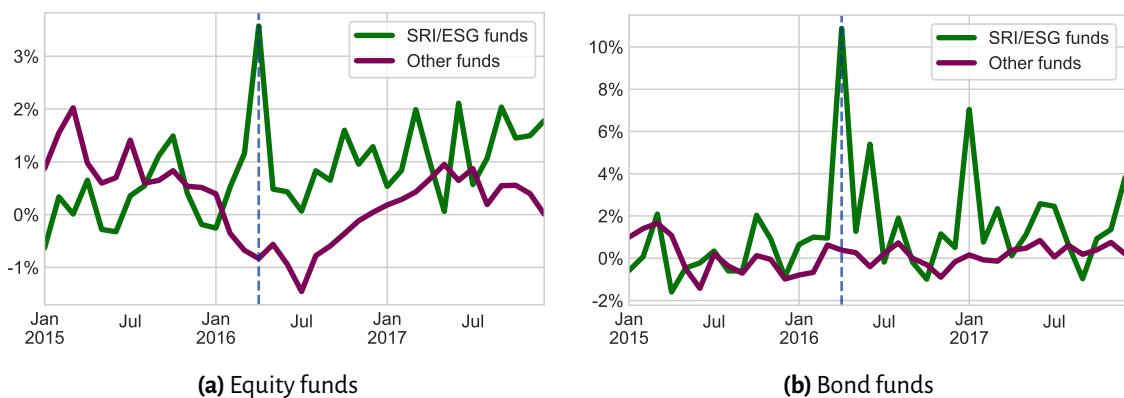


Figure 8: Flows from investment funds to the euro area centred around the signature of the Paris Agreement, separating bond funds and equity funds, with a decomposition between those that classify as ESG/SRI and the rest. Vertical lines correspond to the signature of the agreement (April 2016). Note that no effect can be clearly observed around the drafting period (November-December 2015) or when the agreement took effect (November 2016, which also overlaps with the election of Donald Trump in the United States).

Source: EPFR and authors' calculations.

The existence of a strong positive inflow shock also matters here and does not mechanically

result in a desirable outcome. Coval and Stafford [37] find that extreme inflows can be costly for mutual funds as they tend to increase their existing positions, creating additional price pressure on the holdings common with their peers. In the case of climate shocks, while steady positive flows could ease the financing of the green economy, abnormal inflows to green funds could be less useful, providing instead trading opportunities to outsiders. To that extent, there is a social cost to these sudden shocks, even in their positive materialisation. Existing barriers can reinforce that effect in the case of green funds. In particular, the information acquisition related to screening for green assets can be costly or take long to proceed. Additional monitoring for green features can add to the burden of these funds, when compared to conventional funds that do not have this dimension. Thus, portfolio extensions are difficult to carry in the short term.²⁶ This, in turn, can be alleviated via a greater transparency: cheaper or more readily available information on green factors. Improved regulation regarding carbon disclosure related to financial assets could especially enhance the ability of green funds to react to positive shocks.

Results for this first exercise are given in figure 9, supposing that redemptions occur based on the portfolio carbon rating of the funds. More precisely, to replicate features of the shocks previously described, we suppose the following net flows on the different quintiles of funds when ordered from green to brown: 1%, 0.5%, 0%, -1%, and -5%. The distribution itself is based on the carbon-weighted assets by fund from equation (10), and the percentage changes correspond to values Ψ_i as defined in section 2.4. This results in moderate returns overall, with a stronger amplification of the positive shock through price impact. In line with results obtained in section 4.1 we find that second round gains from cross-holdings are of smaller magnitude than the gains from price impact, except for non-classified funds as they do not suffer from self-inflicted price impact.

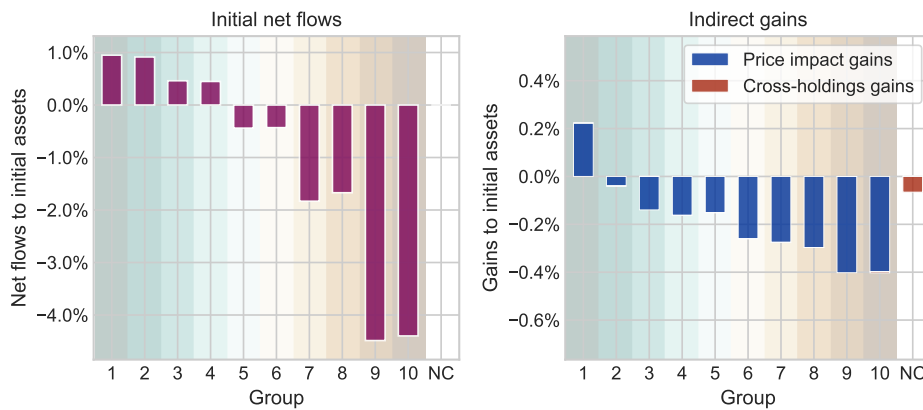


Figure 9: Results for a scenario with carbon-based redemptions.

Funds are ordered by green deciles, i.e. group 1 corresponds to those whose carbon intensity is in the 10% lowest. The group NC corresponds to funds that are not classified from their carbon intensity because the part of their portfolio with corresponding information available is too small. The left-hand chart corresponds to the input to the model, i.e. it is directly determined by the flow ratios of the shock. The right-hand side describes the indirect gains happening as a reaction to initial flows.

Source: authors' calculations.

²⁶The fire sales step introduced in 2.5 is consistent with it, as the extension of portfolios takes priority over the purchase of new assets.

4.3 Transition shock affecting asset prices

In a second scenario, we consider a shock on market prices driven by transition risk, and reinforced by redemptions through a flow-performance response. This supposes the materialization of a transition shock such that investors, for example retail-driven, disinvest from highly polluting sectors and from funds whose carbon intensity is high. This could also reflect for instance an unexpected policy shock. The analysis of transition shocks of the sort has been conducted for instance by Belloni et al. [15], who simulate the impact of short-term credit downgrades from sector-level carbon exposure on banks.

We elaborate a deterministic price shock on securities based on their corresponding carbon intensities, such that brown securities depreciate while the price of greener securities increases. To that end, we use CSDB price data to fit Student-t distributions to all series of monthly prices where securities have more than two year of data available. From this fitting exercise, for every security ω where data on prices is available we derive a function $Q_\omega: [0, 1] \rightarrow [-1, 1]$, which is the quantile function modified to limit the outcome interval.²⁷ Then, if carbon intensity information is available for ω , the shock to its price is computed as $\Lambda_\omega = (Q_\omega \circ \mathcal{D}_g)(\omega)$, where $\mathcal{D}_g: \Omega \rightarrow [0, 1]$ is a shock mapping, decreasing in g_ω , which associates to each security a point on its return distribution. Details of the shock are given in appendix C.1. In the case of securities where carbon intensity is available but not the price distributions, the shock is proxied from securities with the closest characteristics.

Bolton and Kacperczyk [22] find that only the level of emissions matters in the observed carbon premium, and that this is based on scope 1 emissions only. This is supported by Ehlers et al. [42], which find that transition risk corresponding to scope 2 emissions are not appropriately factored by banks in spite of their relevance. Therefore, by using a measure of scope 2 emissions we depart from the already observed dynamics, toward a narrative where markets start reacting to more exhaustive information about their carbon contribution than what is currently the case. Thus, the shock is consistent with a market that corrects for its previous lack of data exploitation. Moreover, Bessec and Fouquau [18] observes from textual analysis the influence of a green sentiment on the financial market, confirming that a reaction is often to be expected relative to climate news. A last narrative consistent with our shock generation is that of Reinders et al. [83], which conducts a stress-test based on the Merton pricing equations. It relies crucially on the past volatility of the asset, as well as on the contemporaneous valuation of the firm, which is also informed by the expected reaction to a carbon tax increase. Our framework is conceptually consistent as past market movements (notably volatility) are used to calibrate return distributions, and the joint use of the portfolio carbon intensity would reflect the change induced by a policy in the market's perception of a firm's value.

In combination with this shock, we use the flow-performance relationship described in 6. We make the conservative hypothesis of null flows in the absence of returns, i.e. $\forall i, q_i = 0$ and the sensitivities to return are calibrated based on the flow-performance study of Renneboog et al. [84]. More specifically their results isolate funds with green screenings from the rest. For a conventional open-end fund i (meaning not green), its sensitivity coefficients are $\tau_i = 1.557$ and $\varsigma_i = 0.553$. Meanwhile, if i is green then $\tau_i = 2.316$ and $\varsigma_i = 0.546$. In particular, this specification reflects for all funds the convex character of the flow-performance relationship, which is observed across most

²⁷The lower bound allows for complete defaults while preventing prices to go negative, and as we do not model large positive shock the upper bound prevents large returns that could be driven by data imperfections. Moreover, this roughly corresponds to the 1% highest absolute monthly returns.

studies.

Results for this exercise are provided in figure 10. Direct gains are overall consistent with the categorization of funds, as the browner ones lose more. The subsequent investment flows are in line with it, and demonstrate the convexity of the relation, as net gains entail a relatively stronger reaction than negative ones. Indirect gains are an order of magnitude lower than direct ones, hence an overall moderate amplification. We see that gains on cross holdings are negative for all categories of funds in the first round, which confirms the possibility of a contagion through this channel, and this is true across most other months with data. Market gains (from price impact) are broadly in line with the sign of the initial shocks, except for the greenest decile, which suffers from negative spillovers.

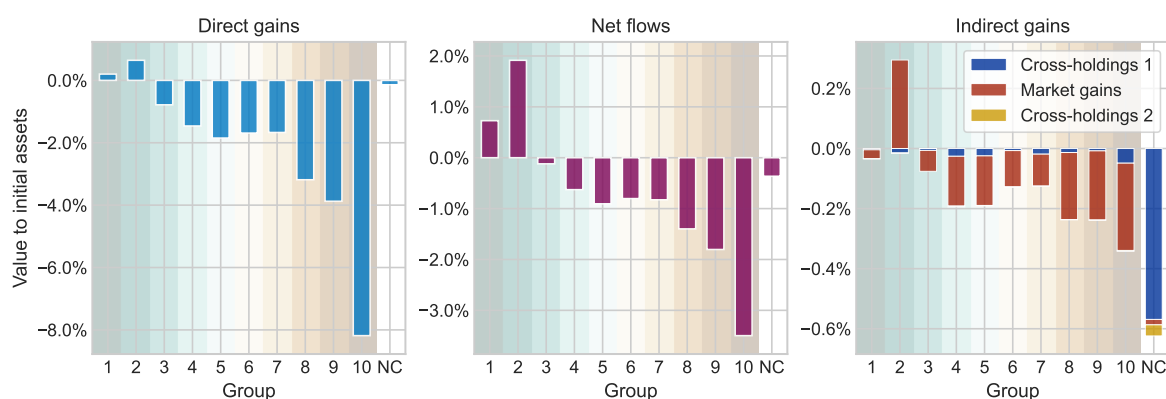


Figure 10: Results for a scenario with carbon-based market shock.

Funds are ordered by green deciles, i.e. group 1 corresponds to those whose carbon intensity is in the 10% lowest. The group NC corresponds to funds that are not classified because the part of their portfolio with carbon intensity information available is too small.

Left panel: direct gains of funds on their portfolio of tradable holdings as entailed by the initial price shock. The aggregation at the decile level is obtained by summing total gains in a decile, and dividing by the sum of initial assets. Central panel: net flows to each decile of funds due to the flow-performance investor reaction. Right panel: indirect gains happening as a reaction to the initial shock and the subsequent flow-performance investment.

Source: authors' calculations.

Crucially, flows to green funds are very strong in case of positive returns, thus the intermediary reaction of investors will reinforce positive spillovers in that case. Therefore, embedding the convex feature of the flow-performance relationship appears key in a setup where we deal with shocks that are complex in nature, i.e. more sophisticated than the uniform stressing approach. Moreover, the effect from the second round of changes on cross-holdings is again significant for non-classified funds only, which also present a large reaction to the first round cross-holdings changes. This can be explained by the fact that many funds are non-classified because they are funds of funds – or at least a large part of their portfolio is made up of other funds – so that by nature they are more affected by this step.

We find $IS(\Lambda) = 0.66$, meaning that it is overall less severe than a uniform shock of a similar first order impact. The series of values for the relative severity of this exercise at different times is given in the appendix, figure 17a. We observe that the indirect severity has some changes, but it is always clearly below 1. Moreover, the trend over the sample period is overall decreasing, which may reflect an increased specialization of funds with regard to carbon intensity metrics.

4.4 Results from physical risks market reaction

As a first result related to physical risk we suppose an improved pricing by the market, such that the price of securities more exposed to physical risk decreases, while some securities at the other end see positive returns. Similarly to the previous market shock, we define a heterogeneous shock between assets based on the physical risk exposure: $\Lambda_\omega = (Q_\omega \circ \mathcal{D}_h)(\omega)$, where $\mathcal{D}_h: \Omega \rightarrow [0, 1]$ is a shock mapping, decreasing in h_ω , that associates to each security a point on its return distribution (details in appendix C.1). We use the same flow-performance calibration as in section 4.3.

Results for this exercise are provided in figure 11. The first key fact is that the coverage of physical exposures is worse than for carbon intensity. Therefore, fewer securities are stressed, explaining that losses appear moderate, although the ones that are stressed suffer shocks of the same magnitude as in the transition risk market shock. From the representation of direct gains, we can first observe that the shock is more equally distributed across funds from different segments compared to the transition market shock, to the point that funds in the first two deciles incur more losses than those of deciles 3 to 7 in relative terms.

This counter-intuitive allocation of the shock has several explanations. First, this sheds light on the fact that funds do not organize or define their portfolio as a function of exposure to physical risks currently. This is to the contrary of carbon exposure, such that a shock based on physical risk is more similar to a shock randomly distributed. Therefore, the difference in *ex ante* physical risk exposures of funds is small (see table 15b in the appendix). Second, the volatility of assets matter: in our setup a very volatile asset with a risk score of 50 can lose more value than a stable asset whose issuer has a risk score of 60. For instance, a fund holding equity securities of mildly exposed firms can lose more than a fund holding bond securities of very exposed firms. Lastly, a bias in our representation comes from the fact that the shock is computed over the total assets of the funds, while the shock hits only part of them. Thus, a fund that holds numerous securities with no exposure information (like sovereign bonds, see table 1), will amortize the shock better and exhibit a smaller relative loss, even if its corporate holdings are very exposed to physical risk.

The net flows observed are all negative, following closely the initial impact, as expected. Then, second round effects seem broadly in line with the initial shock, with the notable fact that non-classified funds that had little direct losses are the ones losing most indirectly. We get $IS(\Lambda) = 0.96$, also meaning that such a shock causes less indirect damages than a flat out crisis, but is close to it because as explained above there is a lesser correlation with the network structure. The full time series is provided in the appendix, figure 17b, where we observe that indirect severity for this exercise is in the window of 91% to 97%, which is higher than that from the transition risk market shock but always below 1.

This lesser absorbance of the shock by the system can be understood in the framework given by Pástor et al. [80], whereby the introduction of ESG and climate risk concerns imply a four-fund separation for investors: a riskless asset, a market portfolio, an ESG weighted portfolio, and a climate risk weighted portfolio. While ESG and climate risks can be correlated in their framework, they can also be more orthogonal if we take the latter as reflective of physical exposure. In our case, the results suggest that while a carbon-weighted portfolio – akin to an ESG one – could be a structuring element of our system, there is no such thing as a common climate risk portfolio that would be used to hedge physical risk. This could be attributed to both a weaker investor preferences and to a lack of information at the firm level.

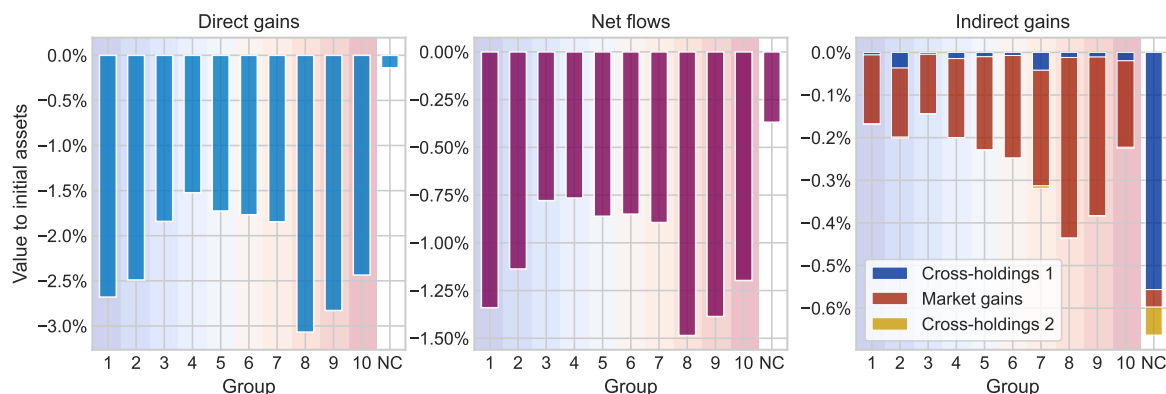


Figure 11: Results for a scenario with a market shock based on physical risk exposure.

Funds are grouped by deciles based on their prior risk exposure, i.e. group 1 is the category whose prior exposure to physical risk is in the lowest 10%. The non-classified (NC) category contains all funds for which less than 20% of their portfolio has a known physical exposure.

Left panel: direct gains of funds on their portfolio of tradable holdings as entailed by the initial price shock. Central panel: net flows to each decile of funds due to the flow-performance investor reaction. Right panel: indirect gains happening as a reaction to the initial shock and the subsequent flow-performance investment.

The aggregation at the decile level is obtained by summing net gains in a decile, and dividing by the sum of initial assets. Because securities with unknown risk are not stressed, the NC category also suffers benign direct losses.

Source: authors' calculations.

4.5 Results from physical risk damage materialization

Beyond their immediate impact, physical shocks from extreme weather events affect the economy through channels such as income destruction, credit shrink or defaults [74, 88]. Under this scenario, the shock materializes in two steps. First, a connected series of extreme weather events occur. This causes a loss of profitability or complete default for firms as they lose part of their physical assets or are impaired in their operations, because their immediate environment or segments of their supply chain are affected. Second, the asset prices decline based on this event and its perception by financial markets [78].

Investment funds are in general not likely to be the sector most affected by such shocks in comparison to banks or insurance undertakers that would lose on their loans to SMEs or would have to directly compensate victims respectively. However, because funds do not seem currently to integrate that dimension in their portfolio choices, a shock from a physical climate event large enough to cause market turmoil could hit them hard. The literature for stress testing short-term climatic events is scarce thus far, but studies such as Mandel et al. [70] in the case of floods show that shocks could be propagated and amplified by the domestic and international banking systems, especially in the future in the case of insufficient adaptation. Therefore, this could push the financial system in a stressed position where funds would be hit too, and other sectors are even more stretched and cannot absorb it. Moreover, Lanfear et al. [68] has documented an important sensitivity to extreme weather events of asset returns, and Billio et al. [19] described an asymmetric exposure of sectors in the European real economy to extreme weather events.

The simulations performed are divided into the different kind of physical risks considered: floods, heat stress, hurricanes/typhoons, water stress, and wildfires. For each run, an issuer-level shock is determined randomly such that $-\Lambda_\omega = \min(x_{f(\omega)}y_\omega, 1)$ where $f(\omega)$ is the country of the issuer of ω , $x_{f(\omega)} \sim U([0, 1])$, and $y_\omega \sim \text{Exp}(100/h_{\omega,k})$ is an issuer level shock given by an exponential

distribution whose mean is the known exposure $h_{\omega,k}/100$ to a source k of physical damage. Thus, we perform a series of Monte Carlo simulations such that each run corresponds to a scenario with differentiated shocks between countries, and differences between issuers in a country are informed by the physical exposure to that type of shock.²⁸ The flow-performance calibration of section 4.3 is used again.

Results for this exercise are given in figure 12. We observe that shocks defined in this way can have material effects, with more than 20% of the sector’s equity wiped out in the most extreme cases. Crucially, the changes in equity for the total investment fund sector exhibit different patterns depending on the type of shock that is used. While the difference between shock types is very dependent on the metric initially used in the exposure assessment, and therefore has little comparative power, the spread of values within each shock type is more indicative. Thus, we see that wildfire, water stress and heat stress are the ones where tail events can damage investment funds the most. Nonetheless, this is subject to data biases as some countries are better covered than others.

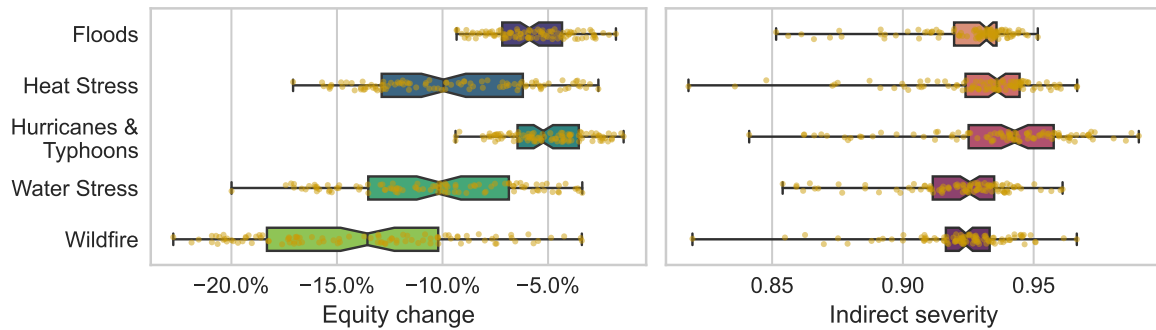


Figure 12: Results for a range of physical shock based on firms’ exposures.

The box plots and scatter plots correspond for each shock category to a total of 100 Monte Carlo simulations, produced from shocks generated based on exposures to physical risks. Notches on the box plots represent the confidence interval around the median. Left panel: total equity change of the sector, i.e. after summing over all funds, in the course of the simulation. Right panel: indirect severity of the simulations, i.e. the level of indirect damages against that of a similar uniform shock, as defined in 4.1.

Source: authors’ calculations.

5 Conclusion and policy discussion

In this paper, we have developed a model to assess the amplification of financial shocks happening within the sector of investment funds on an international scale. The method presented innovates in its formalisation of the shock transmission, including consistently a global sample of open-end and closed-end investment funds.

In our application to climate stress, we assessed the amplification effects from different types of climate shocks that are likely to materialize in a short time frame. These shocks are based on either transition or physical risk and built on a range of plausible narratives. With shocks in line with historical data on investor flows and returns, we find that the initial climate-related shocks can be large. Moreover, second-round effects appear more muted but still sizeable in some cases, while taking into account within-sector amplification only. The amplification is limited for climate

²⁸The stochastic approach to physical risk is also in line with what Budnik [24] advocates for, in the case of climate banking stress tests.

transition risk – with little spillover from the brown funds to the more sustainable ones – but higher in case of shocks based on climate physical risk. This suggests that the network structure is resilient to the type of regulatory or policy shocks associated with a low-carbon transition, but does not adequately mitigate physical risk while it is poised to become a key source of damages.

Crucially, there is currently *no joint mitigation* of climate risk, which leaves the door open to larger future losses. Our data analysis confirms that exposures are significant and that the short-term amplification may be reinforced in the interaction with other financial institutions. Ulterior shocks could still occur and propagate over a short time frame (e.g. future extreme weather events), hence the importance of understanding such contagion dynamics, though the network structure may further evolve. Thus, our results highlight the importance of monitoring the resilience to physical risk, due to the increasing likelihood of “green swans”, i.e. climate events with sufficient disruption potential to trigger a financial crisis [21]. Moreover, hedging climate risk as a whole requires dedicating attention to both transition and physical risk as there is no strong correlation between them.²⁹

For climate transition specifically, the shocks applied mostly stem from an insufficiency of the current regulations. Indeed, as environmental practices and reporting are not sufficiently streamlined, markets suffer from uncertainty in their estimates of climate risk, even in the optimistic case where they would be willing and capable to factor it in. This makes the market still prone to a form of “climate volatility” from the enactment of subsequent regulations. On top of issues in certifying green actors, the public push for the development of green firms is also often lagging. Most of the transition shocks that can plausibly happen in our time frame relate to this currently existing gap. To encompass more of these concerns, we provide in Appendices C.2 and C.3 additional analysis that deals with shocks based on best-in-sector preferences and a “green bubble” narrative.

A convergence of the standards applied by regulators and market data providers would hopefully relieve part of this uncertainty.³⁰ In March 2021, the Sustainability Related Financial Disclosure Regulation entered into force in the European Union. It goes some way in that direction by setting higher transparency and disclosure standards for financial market participants. However, it falls short of providing a really holistic approach, leaving out direct engagement and proxy voting (on top of other implementation flaws). In practice, IMF [60] finds that funds increasingly support climate-related resolutions and that this is more driven by those with an “environmental” label, and less aligned with portfolio composition. In the medium term, a more multidimensional approach might at least mitigate the relative impact of uncertainty from individual sources.

Accounting better for financial cross-holdings would be a necessary complement of this convergence. Indeed, as investment funds by themselves are not carbon intensive, they often tend to bring down the carbon intensity of portfolios. This currently constitutes a form of greenwashing as some funds can invest in other funds browner than them with no negative consequences on their ratings. As we have seen, this particular channel can also reinforce risk as funds that should be greener can then suffer when carbon-intensive assets lose value. These considerations extend to other financial institutions: holdings of securities issued by banks or insurance undertakers could be rated based on

²⁹The lack of attention to the issue of physical damages is in line with findings from Naran et al. [77] that adaptation finance still mostly comes from the public sector.

³⁰See for instance Popescu et al. [82], which reviews the current options for investment funds to do so, and Afota et al. [2] that details the action of Banque de France on its own portfolio, also replicable to a large extent by private financial actors.

the issuers' exposures, e.g. if they finance or insure fossil fuel extraction projects, and not only on the carbon footprint of their own operations (which are low, as per figure 14a).

On the side of practitioners, risk mitigation would also be pushing for companies to reduce the risk at the source. The understanding of risks brings the additional question of whether the network structures that are best suited to weather climate shocks are also optimal against more standard risks. Precisely because making the network of investment funds simultaneously resilient to all forms of risk is hard, a crucial avenue for stability improvement is for financial actors to use their influence on firms in their portfolio for them to engage in carbon emissions abatement or to invest in physical risk adaptation. However, there is still a relative lack of formal incentives for funds to consistently engage in climate stewardship. Indeed, proxy voting could be a major way to make an impact, and institutional investors can be effective in pushing companies to disclose climate-relevant information [46].

For future research, a key avenue is the improvement of shock modelling, and in particular the understanding of physical risk. The design of each shock type used in this paper has room for improvement, to provide a more exhaustive exploration of shocks with identified likelihoods. More work has been done in that respect in the case of transition risk [12, 13, 83], but a lot remains to clarify for both transition and physical risk. Although the method to derive shocks from the data ought to be refined, a more important discussion is the standardization and correctness of the data used as an input. Indeed, as discrepancies between providers exist for both categories of climate data used, the variation coming from initial measurement errors compounds with subsequent model uncertainties [20, 52].

Bibliography

- [1] Tobias Adrian et al. *Approaches to Climate Risk Analysis in FSAPs*. IMF Staff Climate Note 2022/005. International Monetary Fund, 2022.
- [2] Amandine Afota, Clément Bourgey, and Benjamin Bonnin. *Responsible investment: an issue of growing importance for the Banque de France and the central banking community*. Bulletin de la Banque de France 4. Banque de France, 2021.
- [3] Spyros Alogoskoufis et al. *ECB economy-wide climate stress-test. Methodology and results*. Occasional Paper 281. European Central Bank, 2021. DOI: [10.2866/460490](https://doi.org/10.2866/460490).
- [4] Manuel Ammann, Christopher Bauer, Sebastian Fischer, and Philipp Müller. “The impact of the Morningstar Sustainability Rating on mutual fund flows”. In: *European Financial Management* 25.3 (2019), pp. 520–553. DOI: [10.1111/eufm.12181](https://doi.org/10.1111/eufm.12181).
- [5] Adrien Amzallag. “Fund portfolio networks: A climate risk perspective”. In: *International Review of Financial Analysis* (2022), p. 102259. ISSN: 1057-5219. DOI: [10.1016/j.irfa.2022.102259](https://doi.org/10.1016/j.irfa.2022.102259).
- [6] ANBIMA. *Comments from the Brazilian Financial and Capital Markets Association (ANBIMA). Re: IOSCO Report: Leverage*. Associação Brasileira das Entidades dos Mercados Financeiro e de Capitais, 2019.
- [7] Sirio Aramonte and Anna Zabai. “Sustainable finance: trends, valuations and exposures”. In: *BIS Quarterly Review*. Bank for International Settlements, Sept. 2021. URL: https://www.bis.org/publ/qrtrpdf/r_qt2109v.htm.
- [8] Bank of England. *Financial Stability Report*. 38. Bank of England, Dec. 2015.
- [9] Yuliya Baranova, Jamie Coen, Joseph Noss, and Pippa Lowe. *Simulating stress across the financial system: the resilience of corporate bond markets and the role of investment funds*. Financial Stability Paper 42. Bank of England, 2017.
- [10] Paolo Barucca et al. “Network valuation in financial systems”. In: *Mathematical Finance* 30.4 (2020), pp. 1181–1204. DOI: [10.1111/mafi.12272](https://doi.org/10.1111/mafi.12272).
- [11] Stefano Battiston, Petr Jakubik, Irene Monasterolo, Keywan Riahi, and Bas van Ruijve. “Climate risk assessment of the sovereign bond portfolio of European insurers”. In: *Financial Stability Report*. European Insurance and Occupational Pensions Authority, 2019.
- [12] Stefano Battiston, Antoine Mandel, and Irene Monasterolo. “CLIMAFIN handbook: pricing forward-looking climate risks under uncertainty”. Available at SSRN 3476586. 2019.
- [13] Stefano Battiston, Antoine Mandel, Irene Monasterolo, Franziska Schütze, and Gabriele Visentin. “A climate stress-test of the financial system”. In: *Nature Climate Change* 7.4 (2017), pp. 283–288. DOI: [10.1038/NCLIMATE3255](https://doi.org/10.1038/NCLIMATE3255).
- [14] Stefano Battiston, Irene Monasterolo, Keywan Riahi, and Bas J van Ruijven. “Accounting for finance is key for climate mitigation pathways”. In: *Science* 372.6545 (2021), pp. 918–920. DOI: [10.1126/science.abf3877](https://doi.org/10.1126/science.abf3877).
- [15] Marco Belloni, Luca Mingarelli, Rafel Moyà Porcel, and Petya Radulova. “Euro area banks’ sensitivity to corporate decarbonisation”. In: *Financial Stability Review*. European Central Bank, May 2020.
- [16] Marco Belloni et al. “The performance and resilience of green finance instruments: ESG funds and green bonds”. In: *Financial Stability Review*. European Central Bank, Nov. 2020.
- [17] Karen L Benson and Jacquelyn E Humphrey. “Socially responsible investment funds: Investor reaction to current and past returns”. In: *Journal of Banking & Finance* 32.9 (2008), pp. 1850–1859. DOI: [10.1016/j.jbankfin.2007.12.013](https://doi.org/10.1016/j.jbankfin.2007.12.013).
- [18] Marie Bessec and Julien Fouquau. “Green Sentiment in Financial Markets: A Global Warning”. Available at SSRN 3710489. 2020.
- [19] Monica Billio, Roberto Casarin, Enrica De Cian, Malcolm Mistry, and Ayokunle Anthony Osuntuyi. *The Impact of Climate on Economic and Financial Cycles: A Markov-switching Panel Approach*. Research Paper Series 3. University Ca’Foscari of Venice, Dept. of Economics, 2021.
- [20] Monica Billio, Michele Costola, Iva Hristova, Carmelo Latino, and Lorian Pelizzon. “Inside the ESG Ratings:(Dis) agreement and performance”. In: *Corporate Social Responsibility and Environmental Management* 28.5 (2021), pp. 1426–1445. DOI: [10.1002/csr.2177](https://doi.org/10.1002/csr.2177).
- [21] Patrick Bolton, Morgan Després, Luiz Awazu Pereira Da Silva, Frédéric Samama, and Romain Svartzman. “Green Swans”: central banks in the age of climate-related risks. Bulletin de la Banque de France 8. Banque de France, 2020.
- [22] Patrick Bolton and Marcin Kacperczyk. “Do investors care about carbon risk?” In: *Journal of Financial Economics* 142.2 (2021), pp. 517–549. ISSN: 0304-405X. DOI: [10.1016/j.jfineco.2021.05.008](https://doi.org/10.1016/j.jfineco.2021.05.008).
- [23] Antoine Bouveret. *Liquidity Stress Tests for Investment Funds: A Practical Guide*. IMF Working Paper WP/17/226. International Monetary Fund, 2017.
- [24] Katarzyna Budnik. “Towards a macroprudential stress test and growth-at-risk perspective for climate-related risk”. In: *Macroprudential Bulletin*. European Central Bank, Oct. 2021.

- [25] Deutsche Bundesbank. *Centralised Securities Database*. Dataset. 2020. DOI: [10.12757/BBK.CSDB.200903-201912.01.01](https://doi.org/10.12757/BBK.CSDB.200903-201912.01.01).
- [26] Fabio Caccioli, Gerardo Ferrara, and Amanah Ramadiah. *Modelling fire sale contagion across banks and non-banks*. Staff Working Paper 878. Bank of England, 2020.
- [27] Laura Capota, Margherita Giuzio, Sujit Kapadia, and Dilyara Salakhova. “Are ethical and green investment funds more resilient?” In: *International Conference on “Statistics for Sustainable Finance”, co-organised with the Banque de France and the Deutsche Bundesbank*. 2022.
- [28] David Carlin, Maheen Arshad, Ian Hurst, Dawn Holland, and Iana Liadze. *Economic Impacts of Climate Change. Exploring short-term climate related shocks for financial actors with macroeconomic models*. UN Environment Programme Finance Initiative, the National Institute of Economic, and Social Research, 2021.
- [29] Marco Ceccarelli, Stefano Ramelli, and Alexander F Wagner. *Low-carbon mutual funds*. Working Paper 19-13. Swiss Finance Institute, 2020.
- [30] Central Bank of Ireland. *Conduct Risks in an Uncertain World*. Securities Markets Risk Outlook Report. Central Bank of Ireland, 2021.
- [31] Katharina Cera et al. “The role of bank and non-bank interconnections in amplifying recent financial contagion”. In: *Financial Stability Review*. European Central Bank, May 2020.
- [32] Sergey Chernenko and Adi Sunderam. *Liquidity transformation in asset management: Evidence from the cash holdings of mutual funds*. Working Paper 23. European Systemic Risk Board, 2016. DOI: [10.2849/538978](https://doi.org/10.2849/538978).
- [33] Édouard Chrétien et al. *Exposures through common portfolio and contagion via bilateral crossholdings among funds, banks and insurance companies*. HCSF Working Paper. Haut Conseil de Stabilité Financière, 2020.
- [34] Rodrigo Cifuentes, Gianluigi Ferrucci, and Hyun Song Shin. “Liquidity risk and contagion”. In: *Journal of the European Economic Association* 3.2-3 (2005), pp. 556–566. DOI: [10.1162/jeea.2005.3.2-3.556](https://doi.org/10.1162/jeea.2005.3.2-3.556).
- [35] Jamie Coen, Caterina Lepore, and Eric Schaanning. *Taking regulation seriously: fire sales under solvency and liquidity constraints*. Staff Working Paper 793. Bank of England, 2019.
- [36] Rama Cont and Lakshitha Wagalath. “Running for the exit: distressed selling and endogenous correlation in financial markets”. In: *Mathematical Finance: An International Journal of Mathematics, Statistics and Financial Economics* 23.4 (2013), pp. 718–741. DOI: [10.1111/j.1467-9965.2011.00510.x](https://doi.org/10.1111/j.1467-9965.2011.00510.x).
- [37] Joshua Coval and Erik Stafford. “Asset fire sales (and purchases) in equity markets”. In: *Journal of Financial Economics* 86.2 (2007), pp. 479–512. DOI: [10.1016/j.jfineco.2006.09.007](https://doi.org/10.1016/j.jfineco.2006.09.007).
- [38] Lara Cuvelier. *Slow burn. Les gestionnaires d’actifs parient contre le climat*. Le classement inaugural 2021 sur les gestionnaires d’actifs et le charbon. Reclaim Finance, Urgewald, Re:Common, Sunrise Project, 2021.
- [39] Teodor Dyakov and Marno Verbeek. “Front-running of mutual fund fire-sales”. In: *Journal of Banking & Finance* 37.12 (2013), pp. 4931–4942. ISSN: 0378-4266. DOI: [10.1016/j.jbankfin.2013.08.013](https://doi.org/10.1016/j.jbankfin.2013.08.013).
- [40] ECB work stream on non-bank financial intermediation. *Non-bank financial intermediation in the euro area: implications for monetary policy transmission and key vulnerabilities*. Occasional Paper 270. European Central Bank, 2021.
- [41] ECB/ESRB Project Team on climate risk monitoring. *Climate-related risk and financial stability*. European Central Bank, 2021.
- [42] Torsten Ehlers, Frank Packer, and Kathrin de Greiff. “The pricing of carbon risk in syndicated loans: Which risks are priced and why?” In: *Journal of Banking & Finance* (2021), p. 106180. ISSN: 0378-4266. DOI: [10.1016/j.jbankfin.2021.106180](https://doi.org/10.1016/j.jbankfin.2021.106180).
- [43] Larry Eisenberg and Thomas H Noe. “Systemic risk in financial systems”. In: *Management Science* 47.2 (2001), pp. 236–249. DOI: [10.1287/mnsc.47.2.236.9835](https://doi.org/10.1287/mnsc.47.2.236.9835).
- [44] ESMA. *Stress simulation for investment funds*. Economic Report. European Securities and Markets Authority, 2019. DOI: [10.2856/27412](https://doi.org/10.2856/27412).
- [45] J Doyne Farmer, Alissa M Kleinnijenhuis, Paul Nahai-Williamson, and Thom Wetzler. *Foundations of system-wide financial stress testing with heterogeneous institutions*. Staff Working Paper 861. Bank of England, 2020.
- [46] Caroline Flammer, Michael W Toffel, and Kala Viswanathan. “Shareholder activism and firms’ voluntary disclosure of climate change risks”. In: *Strategic Management Journal* 42.10 (2021), pp. 1850–1879. DOI: [10.1002/smj.3313](https://doi.org/10.1002/smj.3313).
- [47] Christoph Fricke and Daniel Fricke. “Vulnerable asset management? The case of mutual funds”. In: *Journal of Financial Stability* (2020), p. 100800. DOI: [10.1016/j.jfs.2020.100800](https://doi.org/10.1016/j.jfs.2020.100800).
- [48] FSB. *The Implications of Climate Change for Financial Stability*. Financial Stability Board, 2020.
- [49] Gábor Fukker, Michiel Kaijser, Luca Mingarelli, and Matthias Sydow. *Contagion from market price impact: a price-at-risk perspective*. ECB Working Paper

2692. European Central Bank, 2022. DOI: 10.2866/699153.
- [50] Régis Gourdel, Eduardo Maqui, and Matthias Sydow. *Investment funds under stress*. ECB Working Paper 2323. European Central Bank, 2019. DOI: 10.2866/990022.
- [51] Michael Grill, Luis Molestina Vivar, and Michael Wedow. *The suspensions of redemptions during the COVID-19 crisis – a case for pre-emptive liquidity measures?* Macprudential Bulletin 12. European Central Bank, 2021.
- [52] Linda I. Hain, Julian F. Kölbl, and Markus Leippold. “Let’s get physical: Comparing metrics of physical climate risk”. In: *Finance Research Letters* (2022), p. 102406. ISSN: 1544-6123. DOI: 10.1016/j.fr.l.2021.102406.
- [53] Grzegorz Hałaj. “System-wide implications of funding risk”. In: *Physica A: Statistical Mechanics and its Applications* 503 (2018), pp. 1151–1181. DOI: 10.1016/j.physa.2018.08.060.
- [54] Jon Hale. *Morningstar Low Carbon Designation*. Morningstar Research, 2018.
- [55] Samuel M Hartzmark and Abigail B Sussman. “Do investors value sustainability? A natural experiment examining ranking and fund flows”. In: *The Journal of Finance* 74.6 (2019), pp. 2789–2837. DOI: 10.1111/jofi.12841.
- [56] Jiekun Huang. “Dynamic liquidity preferences of mutual funds”. Available at SSRN. 2020. DOI: 10.2139/ssrn.967553.
- [57] ICI. *Investment company fact book. A review of trends and activities in the investment company industry*. Investment Company Institute, 2020.
- [58] IMF. “Asset Price Fragility in Times of Stress: The Role of Open-End Investment Funds”. In: *Global financial stability report: navigating the high-inflation environment*. International Monetary Fund, Oct. 2022. Chap. 3.
- [59] IMF. *Detailed assessment of observance of the IOSCO objectives and principles of securities regulation*. IMF Country Report 17/404. International Monetary Fund, 2017.
- [60] IMF. “Investment funds: fostering the transition to a green economy”. In: *Global financial stability report: COVID-19, crypto, and climate: navigating challenging transitions*. International Monetary Fund, Oct. 2021. Chap. 3.
- [61] IMF. *United Kingdom: Financial Sector Assessment Program-Financial System Stability Assessment*. IMF Country Report 22/57. International Monetary Fund, 2022.
- [62] IOSCO. *Recommendations on Sustainability-Related Practices, Policies, Procedures and Disclosure in Asset Management*. Final Report FR08/21. International Organization of Securities Commissions, 2021.
- [63] Artjom Janssen, Justin Dijk, and Patty Duijm. *Misleading Footprints. Inflation and exchange rate effects in relative carbon disclosure metrics*. Occasional Studies 1. De Nederlandsche Bank, 2021.
- [64] Hao Jiang, Dan Li, and Ashley Wang. “Dynamic Liquidity Management by Corporate Bond Mutual Funds”. In: *Journal of Financial and Quantitative Analysis* 56.5 (2021), pp. 1622–1652. DOI: 10.1017/S0022109020000460.
- [65] Chotibhak Jotikasthira, Christian Lundblad, and Tarun Ramadorai. “Asset fire sales and purchases and the international transmission of funding shocks”. In: *The Journal of Finance* 67.6 (2012), pp. 2015–2050. DOI: 10.1111/j.1540-6261.2012.01780.x.
- [66] Tristan Jourde and Arthur Stalla-Bourdillon. *Is there a bubble in “green” equities?* Eco Notepad 235. Banque de France, 2021. URL: <https://blocnotesdeleco.banque-france.fr/en/blog-entry/there-bubble-green-equities>.
- [67] Samuel Karlin. *Matrix games, programming, and mathematical economics*. Vol. 1. Mathematical Methods and Theory in Games, Programming and Economics. Addison-Wesley Publishing Company, 1959.
- [68] Matthew G. Lanfear, Abraham Lioui, and Mark G. Siebert. “Market anomalies and disaster risk: Evidence from extreme weather events”. In: *Journal of Financial Markets* 46 (2019), p. 100477. ISSN: 1386-4181. DOI: 10.1016/j.finmar.2018.10.003.
- [69] Andrea Liesen, Frank Figge, Andreas Hoepner, and Dennis M. Patten. “Climate Change and Asset Prices: Are Corporate Carbon Disclosure and Performance Priced Appropriately?” In: *Journal of Business Finance & Accounting* 44.1-2 (2017), pp. 35–62. DOI: 10.1111/jbfa.12217.
- [70] Antoine Mandel et al. “Risks on global financial stability induced by climate change: the case of flood risks”. In: *Climatic Change* 166.1 (2021), pp. 1–24. DOI: 10.1007/s10584-021-03092-2.
- [71] Sini Matikainen, Emanuele Campiglio, and Dimitri Zenghelis. *The climate impact of quantitative easing*. Policy Paper. Centre for Climate Change Economics et al., 2017.
- [72] Ronald E Miller and Peter D Blair. *Input-output analysis: foundations and extensions*. Cambridge university press, 2009. DOI: 10.1017/CBO9780511626982.
- [73] Harun Mirza, Diego Mocerco, Spyros Palligkinis, and Cosimo Pancaro. “Fire sales by euro area banks and funds: What is their asset price impact?” In: *Economic Modelling* 93 (2020), pp. 430–444. DOI: 10.1016/j.econmod.2020.07.020.

- [74] Irene Monasterolo. “Climate change and the financial system”. In: *Annual Review of Resource Economics* 12 (2020), pp. 299–320. DOI: [10.1146/annurev-resource-110119-031134](https://doi.org/10.1146/annurev-resource-110119-031134).
- [75] Irene Monasterolo and Luca De Angelis. “Blind to carbon risk? An analysis of stock market reaction to the Paris Agreement”. In: *Ecological Economics* 170 (2020), p. 106571. DOI: [10.1016/j.ecolecon.2019.106571](https://doi.org/10.1016/j.ecolecon.2019.106571).
- [76] Felix Mormann. “Why the divestment movement is missing the mark”. In: *Nature Climate Change* 10.12 (2020), pp. 1067–1068. DOI: [10.1038/s41558-020-00950-2](https://doi.org/10.1038/s41558-020-00950-2).
- [77] Baysa Naran et al. *Global Landscape of Climate Finance 2021*. Tech. rep. Climate Policy Initiative, 2021.
- [78] Paolo Pagnottoni, Alessandro Spelta, Andrea Flori, and Fabio Pammolli. “Climate change and financial stability: Natural disaster impacts on global stock markets”. In: *Physica A: Statistical Mechanics and its Applications* 599 (2022), p. 127514. DOI: [10.1016/j.physa.2022.127514](https://doi.org/10.1016/j.physa.2022.127514).
- [79] Luboš Pástor, Robert F Stambaugh, and Lucian A Taylor. “Dissecting Green Returns”. In: *Journal of Financial Economics* 146.2 (2022), pp. 403–424. DOI: [10.1016/j.jfineco.2022.07.007](https://doi.org/10.1016/j.jfineco.2022.07.007).
- [80] Luboš Pástor, Robert F Stambaugh, and Lucian A Taylor. “Sustainable investing in equilibrium”. In: *Journal of Financial Economics* 142.2 (2021), pp. 550–571. ISSN: 0304-405X. DOI: [10.1016/j.jfineco.2020.12.011](https://doi.org/10.1016/j.jfineco.2020.12.011).
- [81] Sebastian Poledna, Serafin Martínez-Jaramillo, Fabio Caccioli, and Stefan Thurner. “Quantification of systemic risk from overlapping portfolios in the financial system”. In: *Journal of Financial Stability* 52 (2021), p. 100808. DOI: [10.1016/j.jfs.2020.100808](https://doi.org/10.1016/j.jfs.2020.100808).
- [82] Ioana-Stefania Popescu, Claudia Hitaj, and Enrico Benetto. “Measuring the sustainability of investment funds: A critical review of methods and frameworks in sustainable finance”. In: *Journal of Cleaner Production* 314 (2021), p. 128016. ISSN: 0959-6526. DOI: [10.1016/j.jclepro.2021.128016](https://doi.org/10.1016/j.jclepro.2021.128016).
- [83] Henk Jan Reinders, Dirk Schoenmaker, and Mathijs Van Dijk. “A finance approach to climate stress testing”. In: *Journal of International Money and Finance* 131 (2023), p. 102797. DOI: [10.1016/j.jimonfin.2022.102797](https://doi.org/10.1016/j.jimonfin.2022.102797).
- [84] Luc Renneboog, Jenke Ter Horst, and Chendi Zhang. “Is ethical money financially smart? Nonfinancial attributes and money flows of socially responsible investment funds”. In: *Journal of Financial Intermediation* 20.4 (2011), pp. 562–588. DOI: [10.1016/j.jfi.2010.12.003](https://doi.org/10.1016/j.jfi.2010.12.003).
- [85] Alan Roncoroni, Stefano Battiston, Marco D’Errico, Grzegorz Hałaj, and Christoffer Kok. “Interconnected banks and systemically important exposures”. In: *Journal of Economic Dynamics and Control* 133 (2021), p. 104266. ISSN: 0165-1889. DOI: <https://doi.org/10.1016/j.jedc.2021.104266>.
- [86] Alan Roncoroni, Stefano Battiston, Luis O.L. Escobar-Farfán, and Serafin Martínez Jaramillo. “Climate risk and financial stability in the network of banks and investment funds”. In: *Journal of Financial Stability* 54 (2021), p. 100870. ISSN: 1572-3089. DOI: [10.1016/j.jfs.2021.100870](https://doi.org/10.1016/j.jfs.2021.100870).
- [87] Regina Schwegler, Beatrice Ehmann, and Anik Kohli. *Sustainability Funds Hardly Direct Capital Towards Sustainability. A Statistical Evaluation of Sustainability Funds in Switzerland and Luxembourg*. Greenpeace Schweiz & Luxembourg, 2021.
- [88] Daniel M Schydrowsky. “Prudential regulations for greening the financial system: Coping with climate disasters”. In: *Latin American Journal of Central Banking* 1.1-4 (2020), p. 100010. DOI: [10.1016/j.latcb.2020.100010](https://doi.org/10.1016/j.latcb.2020.100010).
- [89] Gregor Semieniuk et al. “Stranded fossil-fuel assets translate to major losses for investors in advanced economies”. In: *Nature Climate Change* (2022). DOI: [10.1038/s41558-022-01356-y](https://doi.org/10.1038/s41558-022-01356-y).
- [USA] Senate and House of Representatives of the United States of America. *Investment Company Act of 1940. As Amended Through P.L. 115–174, Enacted May 24, 2018*. 2019.
- [90] Adrien Sénecat et al. “The great green investment investigation”. In: *Follow the money* (2022). Ed. by Eric Smit. Last accessed on 07/02/2023. URL: <https://www.ftm.eu/green-investments>.
- [91] PN Shivakumar and Kim Ho Chew. “A sufficient condition for nonvanishing of determinants”. In: *Proceedings of the American mathematical society* 43.1 (1974), pp. 63–66. DOI: [10.2307/2039326](https://doi.org/10.2307/2039326).
- [92] Andrei Shleifer and Robert W Vishny. “Liquidation values and debt capacity: A market equilibrium approach”. In: *The Journal of Finance* 47.4 (1992), pp. 1343–1366.
- [93] Nicholas Stern and Joseph E Stiglitz. *The Social Cost of Carbon, Risk, Distribution, Market Failures: An Alternative Approach*. Working Paper 28472. National Bureau of Economic Research, 2021. DOI: [10.3386/w28472](https://doi.org/10.3386/w28472).
- [94] PV Subrahmanyam. *Elementary Fixed Point Theorems*. Springer, 2018. DOI: [10.1007/978-981-13-3158-9](https://doi.org/10.1007/978-981-13-3158-9).
- [95] Teruyoshi Suzuki. “Valuing corporate debt: the effect of cross-holdings of stock and debt”. In: *Journal of the Operations Research Society of Japan* 45.2 (2002), pp. 123–144. DOI: [10.15807/jorsj.45.123](https://doi.org/10.15807/jorsj.45.123).
- [96] Matthias Sydow et al. *Shock amplification in an interconnected financial system of banks and investment*

- funds*. ECB Working Paper 2581. European Central Bank, 2021. DOI: [10.2866/68326](https://doi.org/10.2866/68326).
- [97] Bence Tóth et al. “Anomalous price impact and the critical nature of liquidity in financial markets”. In: *Physical Review X* 1.2 (2011), p. 021006. DOI: [10.1103/PhysRevX.1.021006](https://doi.org/10.1103/PhysRevX.1.021006).
- [98] Philippe van der Beck. *Flow-driven ESG returns*. Research Paper Series 21-71. Swiss Finance Institute, 2021.
- [99] Koen van der Veer, Eric Klaaijzen, and Ria Roerink. *Shedding a clearer light on financial stability risks in the shadow banking system*. Occasional Studies 7. De Nederlandsche Bank, 2015.
- [100] JJP Veerman and Robert Lyons. “A primer on Laplacian dynamics in directed graphs”. arXiv preprint [arXiv:2002.02605](https://arxiv.org/abs/2002.02605). 2020.
- [101] Robert Vermeulen et al. “The heat is on: A framework for measuring financial stress under disruptive energy transition scenarios”. In: *Ecological Economics* 190 (2021), p. 107205. DOI: [10.1016/j.ecolecon.2021.107205](https://doi.org/10.1016/j.ecolecon.2021.107205).
- [102] Garbrand Wiersema, Alissa M. Kleinnijenhuis, Thom Wetzer, and J. Doyne Farmer. “Scenario-free analysis of financial stability with interacting contagion channels”. In: *Journal of Banking & Finance* 146 (2023), p. 106684. ISSN: 0378-4266. DOI: [10.1016/j.jbankfin.2022.106684](https://doi.org/10.1016/j.jbankfin.2022.106684).
- [103] Yao Zeng. *A dynamic theory of mutual fund runs and liquidity management*. Working Paper 42. European Systemic Risk Board, 2017. DOI: [10.2849/89957](https://doi.org/10.2849/89957).

A Model and method details

A.1 NAV adjustment details

In this section we prove in different steps the results of proposition 1, starting with the formula to compute the final equity.

Suppose that some funds default, with a solvency indicator γ , and that this results in equity vector $\mathcal{E}(\gamma)$. Without yet imposing both to be consistent, we seek to calculate $\mathcal{E}(\gamma)$. Let us denote by $\pi \in \mathbb{R}^n$ the vector of funds NAVs. First, note that in the absence of any fund flows, the NAVs will change from $\pi(t_1)$ to $\pi(t_2)$, such that $\forall i, \pi_i(t_2) = \pi_i(t_1) \times \gamma_i \mathcal{E}_i(\gamma) / E_i(t_1)$, i.e. the change in share price is proportional to the change in equity for a fund i as long as it is solvent. On the other hand, if i is in default then $\pi_i(t_2) = 0$. Thus, the new totals of redeemable assets are

$$\mathbf{R}(t_2) \cdot \iota_n = \mathbf{R}(t_1) \cdot \text{Diag}(\gamma) \cdot \text{Diag} \left(\frac{\mathcal{E}(\gamma)}{E(t_1)} \right) \cdot \iota_n = \mathbf{r}(\gamma) \cdot \mathcal{E}(\gamma).$$

Then, by applying equation (1), the equity identity, at t_2 , and plugging in the previous results we obtain,

$$\mathcal{E}(\gamma) = \mathbf{r}(\gamma) \cdot \mathcal{E}(\gamma) + \mathbf{A}(t_2) \cdot \iota_m + C(t_2) + B - L,$$

which, by rearranging, leads to $[\mathbf{I}_n - \mathbf{r}(\gamma)] \cdot \mathcal{E}(\gamma) = \mathbf{A}(t_2) \cdot \iota_m + C(t_2) + B - L$. Then, in a second step, we show that $\mathbf{I}_n - \mathbf{r}(\gamma)$ is nonsingular under the regularity condition of definition 1. Notice that the regularity can be expressed in different terms as follows.

Lemma 1. *The network of funds is regular if and only if every fund admits an ultimate external investor.*

The latter concept of ultimate external investor can be defined recursively such that, given a fund i , we say that it admits an ultimate external investor if

- either it admits directly an external investor, i.e. one that does not belong to the network of funds, such that $E_i > \sum_j \mathbf{R}_{j,i}$;
- or one of the other funds with a participation in i admits itself an ultimate external investor, meaning that there exists a path $j_1 \rightarrow \dots \rightarrow j_n \rightarrow i$, where $i \rightarrow j$ means that i holds shares of j , such that j_1 has external investors.

Proof. Suppose first that all funds admit an external investor, and suppose by contradiction that there exists a set \mathbb{X} of funds that are all fully owned by their peers in \mathbb{X} . Take any fund $i \in \mathbb{X}$, and consider a path $j_1 \rightarrow \dots \rightarrow j_n \rightarrow i$ from a fund j_1 with a direct external investor. Thus, $j_1 \notin \mathbb{X}$, and by recursion we can show that none of the other along the chain is in \mathbb{X} , because j_k cannot be in \mathbb{X} and have investor j_{k-1} at the same time. We end up with $i \notin \mathbb{X}$, which is a contradiction, and we conclude that the network is regular.

Second, assume regularity and consider $i \in \{1, \dots, n\}$ with no direct external investor. Let $\mathbb{U}(i)$ the set of all direct and indirect investors of i in the set of funds, and $j \in \mathbb{U}(i)$. Then, $\mathbb{U}(j) \subset \mathbb{U}(i)$ as any direct or indirect investor of j would be at least an indirect investor of i . But by regularity not every fund in $\mathbb{U}(i)$ can be held by other funds in it. This means that there is a fund u in $\mathbb{U}(i)$ with investors not in the set. These investors have to be external from what precedes, and they are also indirect investors of i . We conclude that all funds admit ultimate external investors. ■

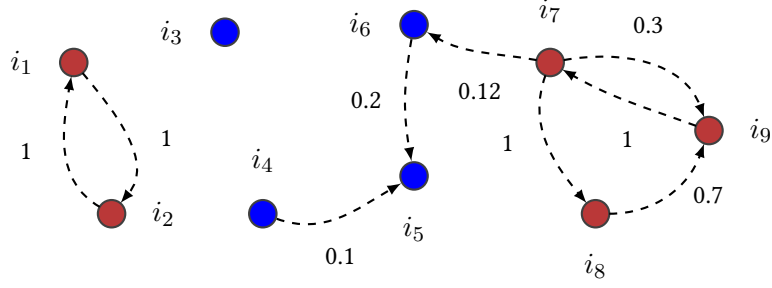


Figure 13: Case of fund system where some funds (in red) break the condition of regularity.

A path $i \rightarrow j$ with weight w means that the fund shares of j that i holds account for a proportion w of j 's equity. In particular, funds that are problematic all belong to non-trivial strongly connected components of the graph.

Without loss of generality, we will assume an absence of defaulted funds at t_1 in the remainder of this section to simplify the notation, so that we consider any $\gamma \in \{0, 1\}^n$. To prove that $\mathbf{I}_n - \mathbf{r}(\gamma)$ is nonsingular, we start by showing that the matrix is (weakly) diagonally dominant,³¹ which results directly from the fact that $\mathbf{r}(\gamma)$ is sub-stochastic, i.e. with columns summing to values between 0 and 1. To that end, consider first that funds do not hold their own shares: $\forall i, \mathbf{r}(\gamma)_{i,i} = 0$. Second, the total value of the shares issued by a fund i should sum up to its equity for an open end fund as long as it is not defaulted. Restricting the shareholders to other investment funds we get $E_i(t_1) \geq \sum_j \gamma_j \mathbf{R}_{j,i}(t_1)$, which gives $1 \geq \sum_j \mathbf{r}(\gamma)_{j,i}$.

Using the regularity condition, we can go further and show that $\mathbf{I}_n - \mathbf{r}(\gamma)$ is a *weakly chained diagonally dominant matrix* (WCDD).³² Indeed, regularity ensures that, in the graph that corresponds to $\mathbf{r}(\gamma)$, if there is no strict diagonal dominance of a row i , it is possible to find a path $i \rightarrow j_1 \rightarrow \dots \rightarrow j_n$ where there is strict diagonal dominance in j_n . Together with the fact that the matrix is weakly diagonally dominant, this defines $\mathbf{I}_n - \mathbf{r}(\gamma)$ as a WCDD matrix. Then, Shivakumar and Chew [91] show that all such matrices are nonsingular.

To prove the reverse for $\gamma = \iota_n$, suppose that there is a set $\mathbb{X} \subseteq \{1, \dots, n\}$ so that each fund in \mathbb{X} is fully owned by other funds in the group. Thus, we have

$$\forall j \in \mathbb{X}, \quad \sum_{i=1}^n \frac{\mathbf{R}_{i,j}}{E_j} = \sum_{i \in \mathbb{X}} \frac{\mathbf{R}_{i,j}}{E_j} = 1. \quad (13)$$

Denote $\iota_{\mathbb{X}} = (\mathbf{1}_{\mathbb{X}}(i))_i$ the indicator vector of set \mathbb{X} . Then, by equation (13) we have $\iota_{\mathbb{X}}^{\top} \cdot \mathbf{r}(\iota_n) = \iota_{\mathbb{X}}^{\top}$, implying that 1 is an eigenvalue of $\mathbf{r}(\iota_n)$. It follows that $\mathbf{I}_n - \mathbf{r}(\iota_n)$ is singular.

Note that regularity is implied by particular cases that can be more straightforward to verify than the original property:

- when every fund has a direct external investor (case of strict diagonal dominance, where the Levy-Desplanques theorem is applicable),

³¹The same result can be obtained from fields other than linear algebra. First, it is known in input-output analysis, with an equivalent proposition in Karlin [67, theorem 8.3.2], a result that describes cases where the Leontief matrix is well-defined, also related to the Hawkins-Simon conditions [see for instance 72]. It can also be obtained from spectral graph theory. Then, \mathbf{X} can be identified as a strict generalized random walk Laplacian in the sense of Veerman and Lyons [100], meaning a matrix of the form $\mathbf{I}_n - a \cdot S$ where $a \in \mathbb{R}^n$, with $a < \mathbf{I}_n$ and $S \in \mathbb{R}^{n \times n}$ is a (row) stochastic matrix, corresponding to the normalized adjacency matrix of the graph of the fund system.

³²It is more general than the case of a strictly dominant diagonal and encompasses it. Note that these notions are often defined from taking row-wise sums, but invertibility is unchanged when considering the transpose.

- or when no cycle exists in the inter-funds cross-holdings (then finding a topological order yields ultimate investors for all funds). This case corresponds to the situation where the step-wise computation of Chrétien et al. [33] ends in finite time.

Finally, it remains to prove that there exists a set of default that guarantees equilibrium. This step is similar to papers in the strand of Eisenberg and Noe [43], with the exception that we have cross-holdings, not liabilities, i.e. a stock approach instead of flows and clearing payment between agents. In this, it is more similar to Barucca et al. [10], except that our underlying mathematical argument relies on the contraction principle instead of the Knaster–Tarski theorem.

Let $M = \mathbf{A}(t_2) \cdot \iota_m + C(t_2) + B - L$. We define $\Phi: \mathbb{R}^n \rightarrow \mathbb{R}^n$ the mapping given by

$$\Phi(e) := \mathbf{r}(t_n) \cdot e^+ + M .$$

We show that this mapping is a contraction for $\|\cdot\|_2$ under the assumption of network regularity. Let $e_1, e_2 \in \mathbb{R}^n$, then

$$\begin{aligned} \|\Phi(e_1) - \Phi(e_2)\|_2 &= \|\mathbf{r}(t_n) \cdot (e_1^+ - e_2^+) + M - M\|_2 \\ &\leq \|\mathbf{r}(t_n)\|_2 \cdot \|e_1 - e_2\|_2 . \end{aligned}$$

Then, we know that $\mathbf{r}(t_n)$ is the transpose of a substochastic matrix, and we have shown that under the assumption of a regular fund network it does not admit 1 as an eigenvalue. Therefore, its largest eigenvalue has a norm strictly less than 1. This is enough to conclude that $\|\Phi(e_1) - \Phi(e_2)\|_2 < \|e_1 - e_2\|_2$, i.e. Φ is a contraction. Given that \mathbb{R}^n is a complete metric space we can conclude from the contraction principle that Φ admits a unique fixed point [94]. Then, denoting as $E(t_2)$ this fixed point we define $\gamma^* = (\mathbf{1}_{[0,\infty)}(E_i(t_2)))_i$, and it comes that $\mathcal{E}(\gamma^*) = E(t_2)$. To find this fixed point, we use the *fictitious default algorithm* from Eisenberg and Noe [43], which converges to the solution in at most n steps. The proof relies on the same arguments and is not reproduced here.

A.2 Details of asset sales and purchases given price impact

The approach used to compute the number of securities sold in the fire sales step involves an iteration to a pseudo-equilibrium where the net cash change for funds is as close as possible to the target one. An alternative viable in the context of an iterating model would be to use simply \mathbf{S}^0 and consider the remaining gap as a liquidity shock for the next period.

Let (ι_i) the fund-level cash targets, given as a ratio to total assets and assumed fixed over the simulation horizon. Thus, the total amount that fund i tries to recover in cash from selling assets is given by $\bar{c}_i = \iota_i(E_i(2) + D_i) - C_i(2)$. We adopt here the slicing hypothesis, whereby, except for cash, all assets are treated similarly regardless of their differences in liquidity.³³ This hypothesis is an estimation, although a standard one [see for instance 9], and evidenced in [8, 37, 65]. A more mixed perspective is provided by Jiang et al. [64], according to which the relative preference between selling illiquid or liquid assets first is influenced by the perceived aggregate uncertainty. The proportional expansion happening in case of inflow is also backed by [37].

Let $\mathbf{S}^0 \in \mathbb{R}^{n \times m}$ be the initial tentative volumes sold per fund and security. We assume that only

³³We have excluded assets that are completely illiquid at the point of splitting between \mathbf{A} and B , so that fire sales can be considered for all assets captured in \mathbf{A} .

long positions are sold, and we denote by $\mathbf{A}^+(2)$ the matrix of holdings on long positions. We get

$$\mathbf{S}^0 = \text{Diag} \left(\frac{\bar{c}}{\mathbf{A}^+(2) \cdot \mathbf{1}_m} \right) \cdot \mathbf{A}^+(2).$$

The derivation of the final sales matrix \mathbf{S} starting from \mathbf{S}^0 is done through a heuristic iterative algorithm, extending on that from [96]. It consists in assuming that agents anticipate the price impact and generally sell more than would normally be needed. The objective is to find a pseudo-equilibrium of sales whereby $C(3) - C(2) \simeq \bar{c}$, with the following considerations:

- Due to the price impact, the amount sold may not be sufficient to recover the liquidity wanted after price change, hence a need to increase the volumes sold. Final volumes are then gradually increased until this iterative process reaches a point where the liquidity demand is satisfied.
- On the other hand, funds may want to buy assets because they exceed their cash target, i.e. where $\bar{c}_i < 0$ for some fund i . Then, a positive price impact may cause the value of assets bought to be higher than initially wanted, so the initial investment can be reduced to achieve the effect wanted.
- When purchasing, there is a risk that a proportional extension of the portfolio is limited by the total available on the market. To avoid exceeding market caps, new random holdings are allocated to funds that want to invest further, first by prioritizing securities that correspond to the usual sectors and countries of investment for each fund, and then picked uniformly among all securities available on the market if the first step is not enough.

Although this is not designed specifically to thwart the effect of fire sales from other funds, significant purchases can have a mitigation effect on second-round losses.

A.3 Details of portfolio overlap measures

The measure of portfolio overlap is defined as the cosine similarity of the holdings, in $[0, 1]$ by construction. This measure consists in taking the scalar products of two normalized vectors, which in our case are the vectors of holdings across tradable securities. That is, given i and j two investment funds, we define their portfolio overlap as

$$S_C(i, j) := \frac{1}{\sqrt{\sum_{\omega} \mathbf{A}_{i,\omega}^2} \times \sqrt{\sum_{\omega} \mathbf{A}_{j,\omega}^2}} \times \sum_{\omega} \mathbf{A}_{i,\omega} \mathbf{A}_{j,\omega}. \quad (14)$$

Similarly, with the whole sector as a counterpart:

$$S_C(i) := \left(\sum_{\omega} \mathbf{A}_{i,\omega}^2 \times \sum_{\omega} \sum_{j \in \{1, \dots, n\}} \mathbf{A}_{j,\omega}^2 \right)^{-1/2} \times \sum_{\omega} \left(\mathbf{A}_{i,\omega} \sum_{j \in \{1, \dots, n\}} \mathbf{A}_{j,\omega} \right). \quad (15)$$

It is not the only measure of portfolio similarity available though. For instance, Caccioli et al. [26] use it jointly with a *BinSimilarity* measure, which is an unweighted count of the number of holdings that are common to both institutions' portfolios.

B Data supplements

This section features complementary information and data analysis to understand the breakdown of funds, the allocation of risk exposures and how funds' portfolios are defined in relation to it. It includes the following:

- Table 2 contains information about the sample of funds used in the reference month. Table 2a provides a view of the different types of funds.
- Figures 14a and 14b present the average carbon emissions by sector and the average physical risk by country respectively.
- Tables 15a and 15b present key statistics on investment funds when they are grouped by deciles based on their risk exposure, relative to transition and physical risk respectively.

With regard to how representative our sample is, we can compare the total assets of open-end funds (the large majority) to those reported in ICI [57]. We find that we capture about 57% of their total net assets by end-2019, given a total of \$54.9 Trillion. Based on the count of the number of funds by domicile country provided by the International Investment Funds Association, our sample is biased towards a strong representation of the US relative to other countries.

Note also that funds are not differentiated based on whether they are actively or passively managed. While behaviours might differ between both, we have considered in our modelling a minimal set of assumptions about funds' reactions, keeping the most mechanical ones resulting from liquidity gaps and surpluses. Therefore, we treat both types of funds equally in that regard. Furthermore, as support for the fact that we generally have low leverage, we present below the regulations that govern this aspect in the most important domicile countries of investment funds:

1. In the US, the most important piece of regulation limiting leverage is [USA], with a maximum leverage of one third. It applies to both open-end and closed-end funds.
2. In the European Union and the UK, many funds are classified as UCITS and thus subject to the UCITS Directive, which includes strict limits on leverage. In contrast, alternative investment funds are governed by the Alternative Investment Fund Managers Directive (AIFMD), which does not feature such limits, but leaves the possibility for restrictions to be imposed.
3. In Brazil, a complete credit-taking prohibition is in place, combined with limitations on the use of derivatives, so that leverage as a whole is strictly regulated and limited [6].
4. In China, regulation is imposed by the China Securities Regulatory Commission (CSRC) (see its *Measures for the Administration of Risk Control Indicators of Securities Companies*) and the Asset Management Association of China (AMAC). Both impose restrictions on different segments of non-banks concerning their leverage [59].
5. In Canada, the *National Instrument 81-102* regulation also places limits on leverage, with open-end mutual funds prohibited from borrowing except in particular situations, and ETFs or alternative investment funds having more possibilities but still bounded.

	Total number	Number closed	Portfolio weight (%)
Mutual Funds	16985	1144	66.0
Insurance Funds	2860	7	7.1
Exchange Traded Funds	2766	1	25.1
Pension Funds	1401	7	1.0
Closed End Funds	426	426	0.8
Hedge Funds	6	0	0.0
Investment Trust	2	2	0.0

(a) Types of funds

	Number	Portfolio weight (%)
USA	10970	88.4
Brazil	3735	1.9
UK	1929	1.2
Luxembourg	1687	2.4
China	1054	0.7
Canada	727	1.0
Korea (Republic of)	671	0.1
Ireland	447	1.2
Germany	305	0.3
South Africa	261	0.2
Other	2660	2.5

(b) Domicile countries of funds

Table 2: Key statistics of the investment funds sample, at the reference month of December 2019.

For both tables, we count primary funds, i.e. not share classes. Moreover, the column of portfolio weight represents the market value of assets held by the given category of funds, as a percentage of the value from aggregating over the whole sample. For the right-hand table, only individual countries with more than 250 funds are represented, and the rest is aggregated in “Other”.

Source: Refinitiv and authors’ calculations.

C Results supplements

C.1 Complementary result figures

We first present the details of the shock used in subsection 4.3, based on the market reaction to transition risk. The mapping adopted to generate the shock is of the form

$$\forall \omega \in \{1, \dots, m\}, \quad \mathcal{D}_g(\omega) = \chi_0 + \frac{1}{1 + \chi_1 + g_\omega/\chi_2}$$

where $\chi_0 \in [0, 1)$, $\chi_1 > \frac{1}{1-\chi_0} - 1$, and $\chi_2 > 0$ are real parameters. The function is chosen so that the resulting return quantile appears sensible and in line with the narrative of the shock. The resulting shock is represented in figure 16a.

For the market shock based on physical risk used in subsection 4.4, the mapping used to define the shock is of the form

$$\forall \omega \in \{1, \dots, m\}, \quad \mathcal{D}_h(\omega) = 1 - \kappa_0 - (1 - \kappa_1) \times \left(\frac{h_\omega - \min_\varepsilon h_\varepsilon}{\max_\varepsilon h_\varepsilon} \right)^{\kappa_2}, \quad (16)$$

with $\kappa_0 \in (0, 1)$, $\kappa_1 \in (\kappa_0, 1]$ and $\kappa_2 \in \mathbb{R}_+$. The resulting shock is represented in figure 16b.

C.2 Results from a market shock on browner firms by sector

We investigate in this section an alternative narrative to the one of subsection 4.3, where instead of shocking securities based on their absolute carbon intensity, we consider how polluting they are relative to other firms from the same sector. The narrative is now of a shock that stems from a green investing endeavour by sophisticated investors who use carbon emission information to foster the

least polluting companies of each sector and penalize the most polluting ones. Alternatively, this could stem from an application of more stringent carbon pricing whereby part of the additional cost is passed downstream but such that the most polluting firms within each sector are forced to internalize more of the cost to remain competitive compared to less polluting firms.

In practice, using the sector decomposition as shown in figure 14a, we can assign to each firm a sector position SP_ω , given by the empirical cumulative distribution function of carbon emissions in the sector of ω . Thus, a value close to 0 means that the issuer of ω is part of the greenest firms in its sector, and among the brownest for a SP_ω close to 1. Note that, for about 38% of the sample, the sector information is missing, and these firms are grouped as if forming another sector. Thus, we define the market shock from a quantile mapping function that combines both the within-sector position and the carbon intensity:

$$\Lambda_\omega = (Q_\omega \circ \mathfrak{D}_{\text{Sec}})(\omega), \quad \mathfrak{D}_{\text{Sec}}(\omega) = \chi_0 + \tau (1 - SP_\omega)^{\chi_3} + \frac{1 - \tau}{1 + \chi_1 + g_\omega/\chi_2}, \quad (17)$$

with $\tau \in [0, 1]$ the parameter that governs the relative importance of the within-sector position. For our application, we pick $\tau = 0.8$, to give predominance to the within-sector position.

The shock generated is represented in figure 18a, with a separation between the debt and equity classes. As we would expect, the correlation between the carbon intensity and the shock has become weaker than it was in the initial transition shock of figure 16a. Indeed, securities that are not at the tail of the overall distribution carbon-wise, are now very stressed as they represent the worst polluters in a given sector. Corresponding results are presented in figure 18b. We observe that results present similarities to the initial transition shock, but investment inflows to green funds result in a mild amplification, even for the browner funds.

C.3 Results from a shock on green assets

Recent data on investment funds show that those labelled ESG or SRI are prominent drivers of non-bank growth. This growth of sustainability-labelled funds, which are mostly included in these two categories (where not wrongly assimilated to them), in its steady aspect alone, has raised the concern that green stocks are overvalued³⁴ because they are part of a pool of assets that is too small. Thus, it is argued in van der Beck [98] that strong flows to ESG funds have artificially driven up the price of their holdings over the past years, also in line with a “concern-driven” performance of green securities by Pástor et al. [79]. The implication advanced is that reduced future flows to sustainable funds could harm the price of the highly ESG-rated securities from a lesser purchasing pressure, although this argument is contingent on a broadly unchanged economic framework. For instance, a strong commitment to a rapidly increasing carbon price in the medium term could change the perspective, as could the legal liabilities of firms related to ESG criteria. Nonetheless, given the uncertainty surrounding these developments, a market correction of the price of current “sustainable assets” – i.e. a “green bubble” – cannot be disregarded.

We model the occurrence of a shock on green assets is modelled as the opposite of the transition risk market shock (although with different parameters to avoid a large positive shock on brown assets), i.e. being influenced by both within-sector considerations and absolute carbon emissions.

³⁴Opposite opinions on the matter have been expressed by Aramonte and Zabai [7], looking in particular at the valuations of ESG funds, and by Jourde and Stalla-Bourdillon [66], comparing green to brown assets.

Thus, we get

$$\Lambda_\omega = (Q_\omega \circ \mathfrak{D}_{\text{GB}})(\omega), \quad \mathfrak{D}_{\text{GB}}(\omega) = 1 - \chi_0 - \tau(1 - \text{SP}_\omega)^{\chi_3} - \frac{1 - \tau}{1 + \chi_1 + g_\omega/\chi_2}. \quad (18)$$

The shock thus generated is represented in figure 19a, where we observe a shape opposite to the previous ones, i.e. a net loss on the greenest assets and small gains on assets that are relatively brown. Interestingly, we observe from the results in figure 19b that the impact on funds is more homogeneous than the previous transitory shocks. That is, greener funds tend to lose more, but the losses of brown funds are comparable. Differences between the groups are even smaller at the point of considering the second-round effects. Moreover, the initial shock that we derive here is of relatively small magnitude. The key difference with transition shocks is that short-term dynamics are the only ones likely to materialize. Therefore, this indicates that damages from a “green bubble” would propagate to a large part of the investment funds system but with a limited impact.

C.4 Shock methodology comparison

It is worth comparing the methodology employed here, for the generation of input shocks in particular, to the case study on investment funds conducted in Carlin et al. [28]. While it does not model contagion, [28] is one of the closest works to ours, given its focus sector, its emphasis on the importance of short-term climate stress tests, and having low-carbon assets with positive shocked returns. Using our notation, their methodology can be represented by the following equation:

$$\Lambda_\omega = (\mathfrak{B} \circ \mathfrak{T}_{\text{IC}})(f_{\text{MSCI}}(\text{LCT}_\omega), \text{Sec}(\omega), \text{Country}(\omega)),$$

which is composed of the following:

1. The equity price shock function f_{MSCI} is calibrated using MSCI Low Carbon Transition (LCT) scores.
2. Company-level baseline shocks $f_{\text{MSCI}}(\text{LCT}_\omega)$ are calculated, where LCT_ω is the LCT score of the company issuing ω . Industry-level shocks are then derived as weighted averages from the firms they include.
3. Industry-based and country-based caps/floors are applied (function \mathfrak{T}_{IC}), including a minimum shock to all companies based in a major oil-producing country.
4. Shocks are bucketed to a discrete grid (function \mathfrak{B}).

The price changes then affect nonbanks in their portfolio, similar to our first-round impact.

Aside from having further dynamics in our model following the initial shock, we can identify two features in which our shock generation differs conceptually from [28]. The first one is that their shocks do not depend on the financial properties of the securities, relative to the way we interact carbon emission intensities with the distribution of historical returns, and in particular the variance observed. This reflects a difference in the narrative, whereby we try to better capture a plausible immediate reaction of financial markets, while [28] may be based on a change in fundamentals that moves the market over a somewhat longer time frame.

Second, the choice of applying relatively uniform shocks within each sector is something that is not present in our main simulations presented in Section 4. It is opposed but complementary to the narrative that supports our additional exercise presented in Appendix C.2. Where [28] assume that the market would react primarily on sector information, we assumed that it would respond

given a more accurate data access and favour best-in-class companies. The relative plausibility of both alternatives is not settled and may depend on factors such as the extent to which carbon price increases would be passed on to clients downstream, or the degree of competition existing within a sector.

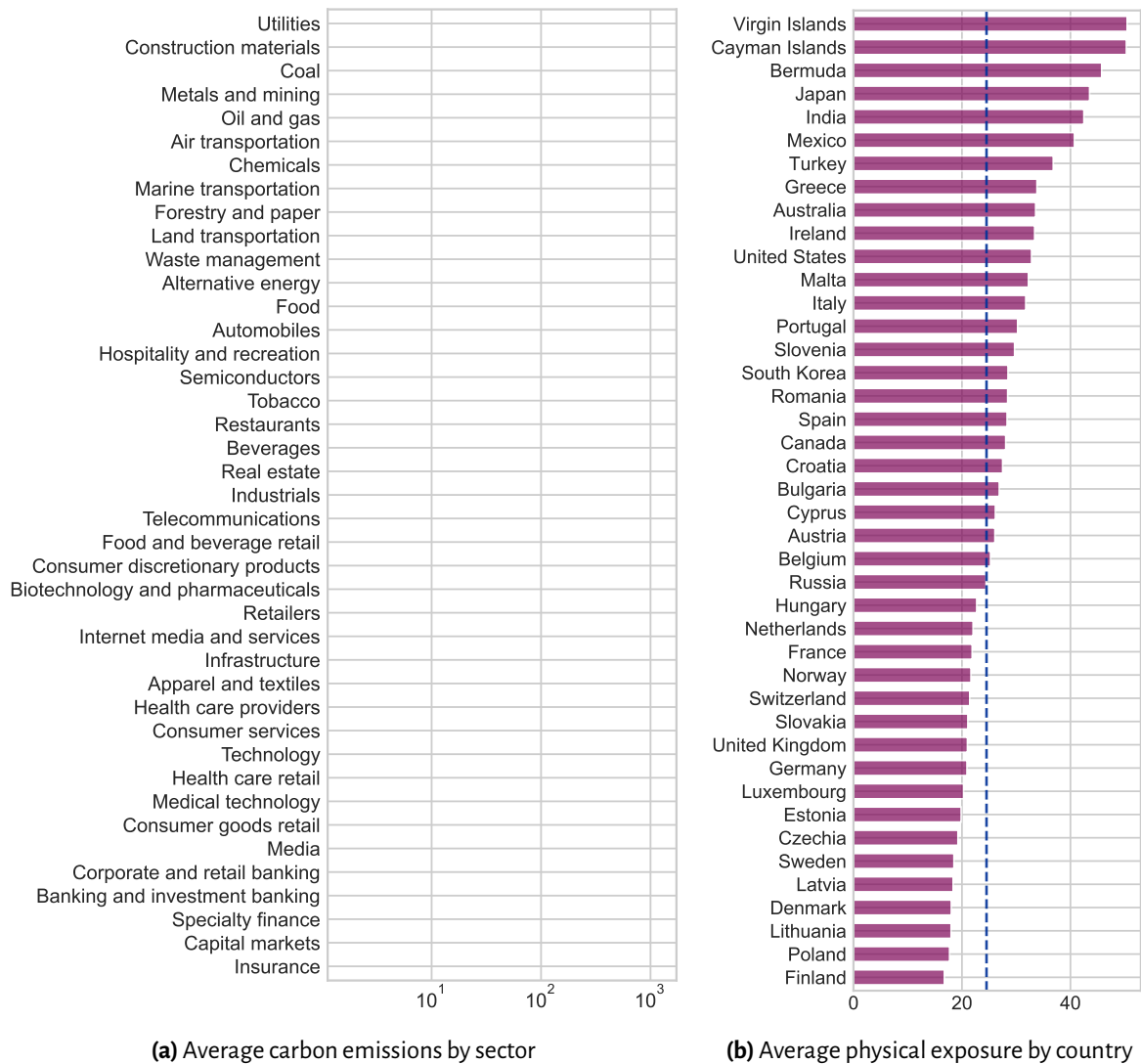


Figure 14: Decomposition of climate data along dimensions of interest.

Left panel: carbon emissions on scopes 1 and 2 (in log scale on the x-axis) by sectors of firms (on the y-axis). Only sectors with more than 50 entities are kept. Additionally, data analysis not presented here shows that there are also marked differences between countries on carbon intensity as some of them host many polluting industries. Right panel: some important variations between countries (on the y-axis) are observed with regard to climate physical risk exposure (on the x-axis). Only countries with more than 100 entities are kept. The blue dashed line represents the euro area average.

Sources: Urgentem, 427 and authors' calculations.

Category	Number of funds	Mean AUM (million euros)	Mean carbon intensity	Category	Number of funds	Mean AUM (million euros)	Mean physical risk
1	1372	2261.8	1.3	1	1205	506.4	21.2
2	1372	1357.3	32.3	2	1205	1028.4	24.4
3	1372	1196.4	55.6	3	1205	1428.3	26.7
4	1372	1172.1	79.6	4	1204	1033.4	28.9
5	1372	1739.2	103.5	5	1205	1604.7	30.5
6	1371	2593.8	129.3	6	1205	2414.9	31.9
7	1372	2552.7	155.5	7	1204	1883.1	33.0
8	1372	1307.0	197.4	8	1205	4245.3	34.1
9	1372	1479.7	270.9	9	1205	1593.6	35.5
10	1372	544.4	623.1	10	1205	1032.9	41.3
NC	9477	637.4		NC	11148	723.3	

(a) Carbon intensity categorization

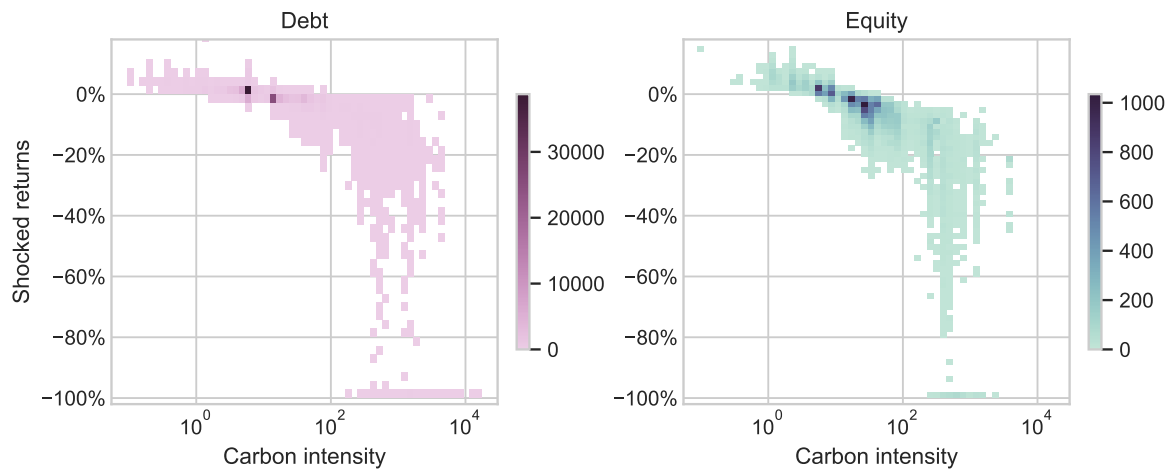
(b) Physical risk categorization

Figure 15: Grouping into deciles of risk as used in the simulation framework.

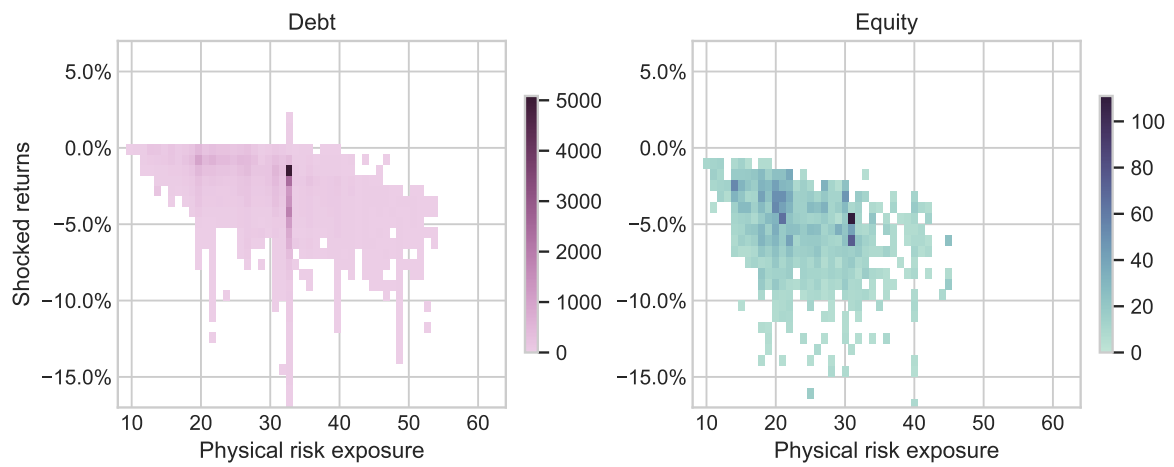
Left panel: all funds whose securities with available carbon ratings represent more than 50% of their portfolio by market value distributed into different deciles. The allocation is based on the fund-level carbon intensities defined by equation (10). Category 1 represents the greenest 10% of classified funds, category 2 the 10% to 20% greenest, etc, and NC includes all non-classified funds (falling below the 50% threshold). The column with mean carbon intensity is an unweighted average across all funds in a category. Note that, although all securities have positive carbon emissions associated, some funds may have a negative weighted average because they short polluting securities.

Right panel: all funds whose securities with available climate physical risk exposure represent more than 20% of their portfolio by market value distributed into different deciles. The allocation is based on the fund-level physical risk exposures defined by equation (11). Category 1 represents the 10% least exposed of classified funds, category 2 the 10% to 20% least exposed, etc, and NC includes all non-classified funds (falling below the 20% threshold). The column with mean physical risk is an unweighted average across all funds in a category.

Source: Urgentem, 427, Refinitiv and authors' computations.



(a) Transition risk market shock



(b) Physical risk market shock

Figure 16: Bi-dimensional histogram of the market shocks used in 4.3 and 4.4, with a decomposition between asset types. The x-axis gives the carbon intensity of the assets while the y-axis gives the shocked returns. The colour of a square corresponds to the number of securities that present the corresponding risk/shock profile. Source: authors' calculations.

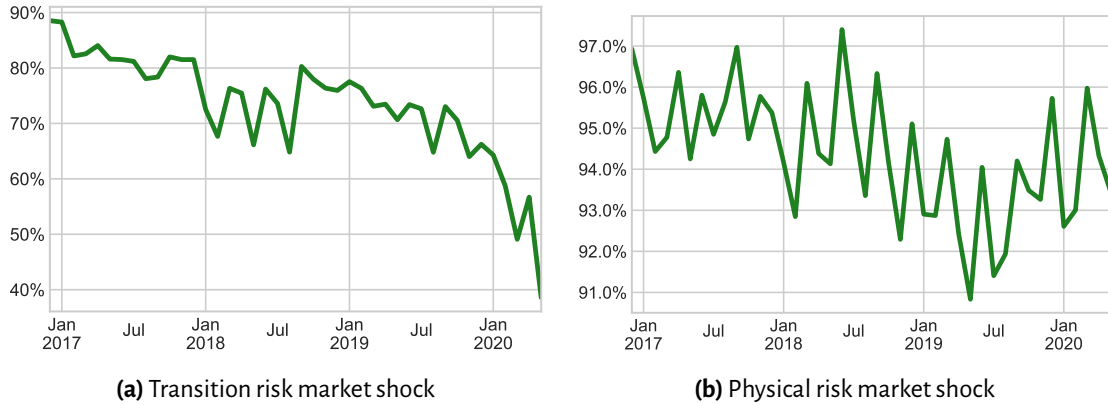
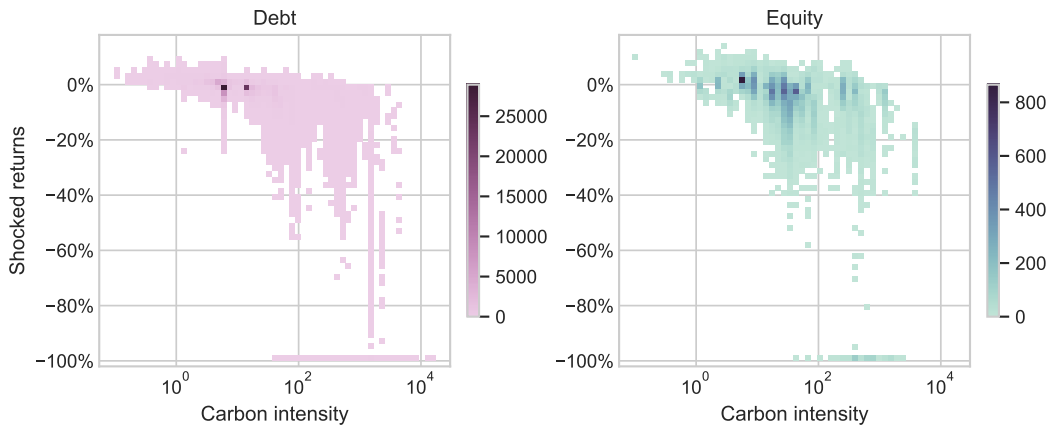
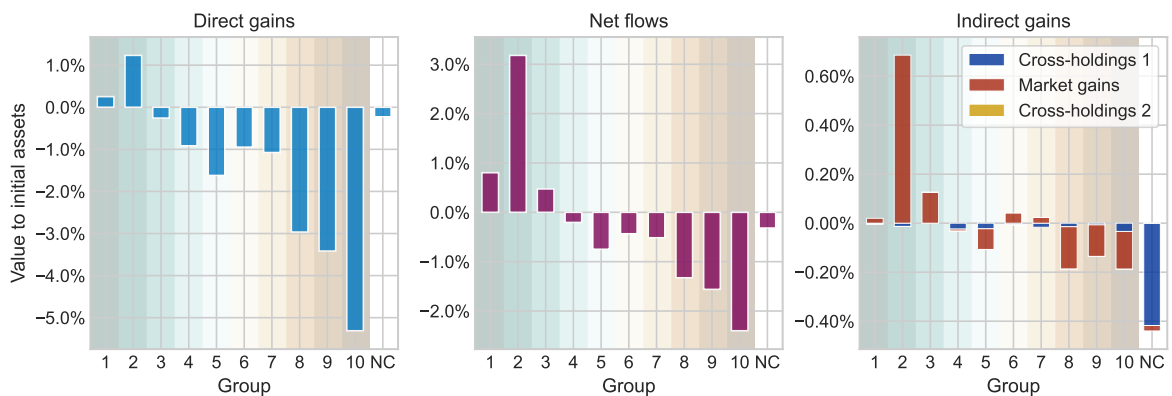


Figure 17: Time series of indirect severity. Left panel: indirect severity for different months, based on the same transition risk market shock used in section 4.3, and represented in figure 16a. Right panel: indirect severity for different months, based on the same physical risk market shock used in section 4.4, and represented in figure 16b. For both, the indirect severity is defined in section 4.1 relative to a uniform shock with a similar aggregate direct impact. Source: authors' calculations.

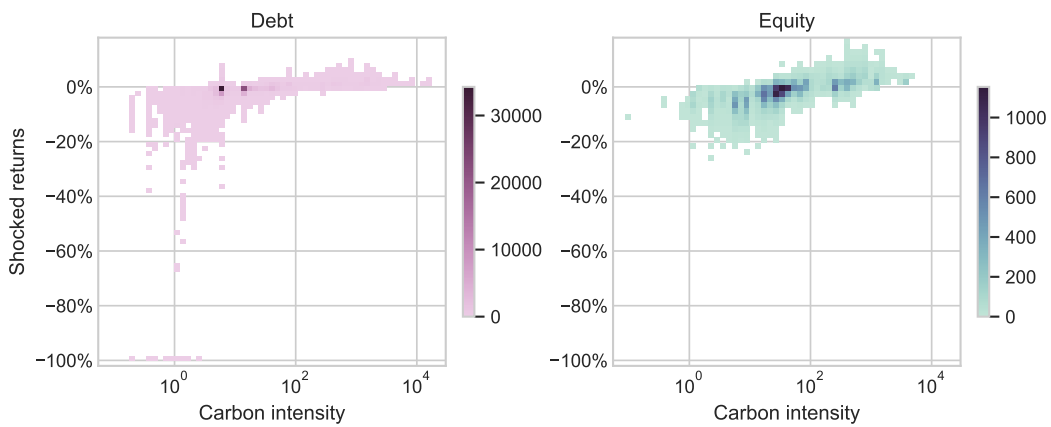


(a) Transition risk market shock

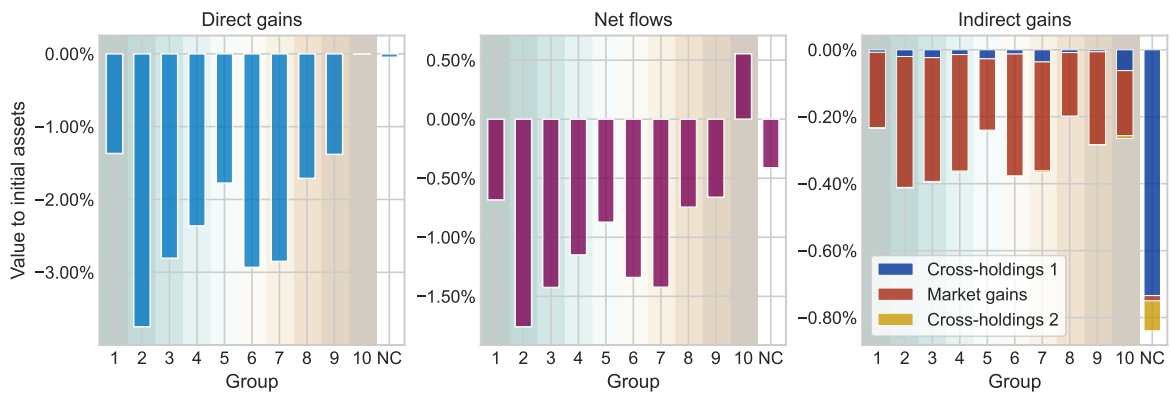


(b) Decomposition of outputs

Figure 18: Shock and results for the simulation penalizing “worst in class” securities. For the upper panel, the x-axis gives the carbon intensity of the assets while the y-axis gives the shocked returns. The colour of a square corresponds to the number of securities that present the corresponding risk/shock profile. For the lower panel, the x-axis corresponds to groups of funds arranged by deciles according to the values of their carbon-weighted assets. The y-axis corresponds to the size of gains and flows relative to the initial value of assets. Source: authors' calculations.



(a) Market shock



(b) Decomposition of outputs

Figure 19: Shock and results for the “green bubble” simulation.

For the upper panel, the x-axis gives the carbon intensity of the assets while the y-axis gives the shocked returns. The colour of a square corresponds to the number of securities that present the corresponding risk/shock profile. For the lower panel, the x-axis corresponds to groups of funds arranged by deciles according to the values of their carbon-weighted assets. The y-axis corresponds to the size of gains and flows relative to the initial value of assets.

Source: authors’ calculations.