ESG Investing:
A Chance to Reduce Systemic Risk

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Abstract

We consider a network of equity mutual funds characterized by different levels of compliance with Environmental, Social, and Governance (ESG) aspects. We measure the impact of portfolio liquidation in a stress scenario on funds with different ESG ratings. Fire-sales spillover from portfolio liquidation propagates from one fund to another through indirect contagion mediated by common asset holdings. The analysis is conducted quarterly from March 2016 through June 2018 using daily data from different sources at the fund and firm levels. Our estimation strategy relies on a network analysis where funds are not taken as stand-alone entities but are interconnected components of a unified system. We find evidence that the relative market value loss of the *High* ESG ranked funds is lower than the loss experienced by the *Low* ESG ranked counterparts in the time span with lower volatility. In the higher-volatility period there is not always a clear dominance of one class over another. Results are robust when controlling for size and for feedback effects, and for different model specifications. Our analysis offers new insights to both asset managers and policymakers to exploit the aggregate effect of portfolio diversification related to the system as a whole.

Keywords: ESG investing, Systemic Risk, Market Impact, Network, Indirect Contagion

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1 Introduction

Systemic events, such as the Lehman Brothers default in September 2008, might generate widespread financial distress across the system. Such instability can be triggered by (1) an exogenous shock that hits several financial institutions at the same time, (2) financial imbalances built over time that collapse at the same time, (3) a negative externality generated in one financial institution that propagates to the others. In the last scenario, we denote the risk of a particularly violent transmission as contagion risk (De Bandt and Hartmann, 2015), that may lead to market crashes.[1]

This paper studies whether (E)nvironmental, (S)ocial and (G)overnance compliance of assets held in portfolio by equity mutual funds mitigates the negative effects of financial distress which propagates from a fund to another. Demand for ESG investing surged in recent years due either to favorable risk/return characteristics of ESG assets (Becchetti et al., 2018), or to the investor preference for such assets unrelated to risk/return considerations (Fama and French, 2007).

Three main aspects motivate our research. ESG investing (1) reduces stakeholder risk, (2) relies on longer investment horizons, and (3) exploits a market segment which is not mainstream. First, ESG investing is associated with a reduction of stakeholder risk. This aspect is related to the stakeholder theory as detailed in Becchetti et al. (2018), where the authors show that firms registering lower ESG scores are more exposed to the risk of future litigation with stakeholders, namely stakeholder risk. Under equilibrium, pushed by investor demand, firms with higher ESG scores decrease their systematic risk (Pastor et al., 2020, Albuquerque et al., 2019). This is related to lower stock expected returns. Moreover, Becchetti et al. (2015b) find evidence that firms with higher Corporate Social Responsibility (CSR) intensity and lower stakeholder risk increase idiosyncratic risk. In line with stakeholder risk reduction, Kim et al. (2014) find that firms with a higher standard of transparency engage in less harmful news hoarding, hence lowering their exposure to crash risk. Similarly, Boubaker et al. (2020) show that firms with higher ESG scores have a lower financial distress risk and, as a result, are less likely to face financial default.

Second, ESG funds rely on long-term investment strategies. Hence, ESG funds are less inclined to sell ESG assets only on their risk/return performance (Ciciretti et al., 2019; Bollen, 2007). Indeed, the demand for ESG assets is driven by investors' preference for such stocks. Those

[1]See Benoit et al. (2017) for an extensive literature review on theories and measures of systemic risk.

investors are reluctant to sell these assets even during crisis periods (Nakai et al., 2016, Becchetti et al., 2015a, and Nofsinger and Varma, 2014). This result can be justified by the existence of a multi-attribute utility function for responsible investors that incorporates their preferences into their investment decisions (El Ghoul and Karoui, 2017 and Bollen, 2007).

Third, funds that are high ESG ranked tilt their portfolios towards those assets having the highest compliance with ESG aspects (Joliet and Titova, 2018). In doing so, they exploit a segment of the market that would be unexplored by other funds. This is consistent with the higher idiosyncratic risk of the high ESG ranked firms documented in Becchetti et al. (2015b). As a consequence, high ESG ranked funds have less overlap with all other funds than do low ESG ranked funds; hence, the risk of contagion from one fund to another might be reduced.

All these aspects characterize the ESG investing industry in terms of a general risk reduction (Albuquerque et al., 2019; Kim et al., 2014). In case of contagion, ESG can mitigate the negative effects in financial markets. In such a scenario, investors' preferences for ESG assets may play a prominent role in lowering contagion risk, and consequently ESG funds could be characterized by the intrinsic property of lowering systemic risk based on the characteristics previously mentioned.

In this strand of literature, Lins et al. (2017) show that firms with high social capital had stock returns that were four to seven percentage points higher than firms with low social capital during the 2008–2009 financial crisis. This result suggests that investing in social capital strengthens the relationship between stakeholders and investors, and that a more substantial relation pays off when the overall level of trust in corporations and markets is affected by a negative shock. Becchetti et al. (2015a) and Nofsinger and Varma (2014) find that ESG funds outperform conventional funds during crisis periods but that the dampening of downside risk comes at the cost of lower returns during non-crisis periods. Hence, ESG investing can be seen as a shield during periods of market turmoil. Similarly, Nakai et al. (2016) find that Japanese ESG funds were better equipped than conventional funds to absorb the negative shock caused by the bankruptcy of Lehman Brothers.

Even though many papers focused on ESG investing during the financial crisis, ESG investing remains an unexplored field of research with respect to networks of interconnected funds. The objective of this paper is to examine whether, and to what extent, funds with different levels of ESG compliance are also characterized by different degrees of resilience to contagion.

We provide an answer to this research question by taking quarterly observations during the period March 2016 to June 2018 of the open-ended equity mutual funds that are ESG ranked by Morningstar. ESG ratings and information at the fund level (Morningstar Direct) are matched with information at the holdings level (Morningstar European Data Warehouse) and at the assets level (Refinitiv) to build a network of funds with different levels of ESG compliance. In such a network, funds are interconnected only indirectly (since funds are not mutually exposed to counterparty risk) through the holdings they have in common. Contagion is then indirectly mediated by the overlap between portfolios, and it is due to fire-sales spillover.

The propagation mechanism works as follows. Initially, a financial institution is forced to liquidate part of the assets in its portfolio due to an exogenous shock. This liquidation creates price pressure in the liquidated securities. In turn, other financial institutions investing in the same securities may experience a loss of value in their portfolios. Such price pressure can eventually force them to liquidate part of their positions as well. Hence, the initial shock may trigger fire-sales spillover which propagates throughout the financial system.

To model indirect contagion, we follow Cont and Schaanning (2019) and Braverman and Minca (2018), who rely on a linear market-impact model (Kyle, 1985). We also measure contagion risk by implementing the non-linear model proposed in Cont and Schaanning (2019) for robustness checks of results. Next, we construct the funds adjacency matrix by computing the common-holdings overlap for each pair of funds in the network. A feature of the model is that any asset impacts differently on portfolio overlap on the basis of its market depth. An asset whose market depth is high, that is, a liquid asset, has a low weight in portfolio overlap since it is less responsible for indirect contagion between funds. Differently, an asset with a low market depth has a large weight in the overlap.

For all cross-sections in our time span, we measure the relative total loss of market value for funds in the top 20% (*High*) and bottom 20% (*Low*) of the ESG score distribution when all funds in the network liquidate a fraction of their portfolios. This quantity is also proportional to the average relative market value loss experienced by funds due to liquidation by one fund at a time.

Our results show that the relative total loss experienced by the *High* ESG ranked funds is lower than that for the *Low* ESG ranked funds in eight out of 10 cross-sections. In the remaining cases, the losses are slightly higher for the *High* ESG ranked funds. We further test the alternative hypothesis that the relative total loss experienced by the *High* ESG ranked funds is different from the relative total loss for the *Low* ESG ranked funds against the null hypothesis that this difference is zero. We accept the alternative in six out of 10 cross-sections, and when the difference is statistically significant, the loss is always lower for the *High* ESG ranked funds. Switching the perspective to interpret results, our sample is characterized by both high- and low-volatility regimes. Specifically, the 2017 and 2018 cross-sections are characterized by lower volatility, and in this scenario the *High* ESG ranked funds always show a lower relative total loss. On the other hand, the 2016 cross-sections show higher volatility without a clear dominance of one class over another. We perform also robustness checks to control for size, to consider different cutoffs of the ESG ranking distribution, to account for the feedback effect in contagion transmission, and to test for non-linear market impact.

Our results add new insights to the literature on ESG funds (Lins et al., 2017; Nakai et al., 2016; Becchetti et al., 2015a; Nofsinger and Varma, 2014), showing that the *High* ESG ranked funds are more resilient to contagion than the *Low* ESG ranked funds under lower-volatility regimes, while in the higher-volatility periods we find mixed evidence.

Furthermore, our empirical analysis contributes to the literature on indirect contagion (Braverman and Minca, 2018; Coval and Stafford, 2007; Flori et al., 2019; Guo et al., 2016) showing that a financial market characterized by a higher degree of responsible investments is less vulnerable to fire-sales spillovers. This is in line with Flori et al. (2019), who represent the relationships between mutual funds and portfolio holdings by using a bipartite network and propose an indicator which measures the degree of overlap of funds in the market. Their findings indicate that funds investing in niche markets have been less affected by the 2008 financial crisis, arguing that such funds were less exposed to fire-sales spillover. Coval and Stafford (2007) analyze the cost of asset fire sales in the equity market caused by mutual funds transactions. Braverman and Minca (2018) measure the overlap between mutual funds by weighting different portfolio holdings with a liquidity factor and propose different measures of vulnerability that are negatively correlated with fund returns. Guo et al. (2016) analyze the liquidity-weighted portfolio overlaps among US funds and find that a higher overlap corresponds to higher negative excess returns when funds liquidate their assets.

From a methodological point of view, we study ESG funds considering also their interrelations, not as stand-alone entities. It is worth citing Bauer et al. (2007), who find that ESG funds significantly underperform conventional funds. Similarly, El Ghoul and Karoui (2017) show that funds' risk-adjusted returns decrease with the level of funds' ESG score. Most of the studies find no statistical difference in performance between ESG and conventional funds. Using a sample of Australian ESG funds, Bauer et al. (2006) find no evidence of significant differences in risk-adjusted returns between ESG and conventional funds during the period 1992–2003. The same results hold using a sample of international funds for the 1990–2001 period (Bauer et al., 2005). Similarly, Renneboog et al. (2008) find that ESG funds underperform their domestic benchmarks but that the result is not statistically significant for most of the countries analyzed when looking at risk-adjusted returns. Remarkably, all the cited papers address ESG funds as individual entities, without referring to their interconnections. We take into account the presence of funds' interdependence when dealing with their risk profiles by introducing a network structure among funds.

The paper is organized as follows. Section 2 introduces the model, constructs the network, and provides a measure of market value loss from portfolio liquidation. Section 3 describes the dataset, compares the market value loss for funds with different ESG ratings, and reports results of the robustness checks. Section 4 concludes.

2 The model

We model the interrelations between funds and their constituencies by using a bipartite network. The network has two different sets of nodes. Nodes in the first set represent funds; nodes in the second set represent their constituencies. A node in the funds set is linked only to the nodes in the assets set representing its holdings. Hence, two funds are indirectly connected through their common holdings.

Indirect contagion is the main channel of risk propagation among mutual funds whose portfolios have in common part of their assets. Indeed, contagion in a network of funds is indirectly mediated by common asset holdings. Let us assume that a fund is forced to liquidate part of its assets due to an exogenous shock. For example, funds experiencing large outflows tend to decrease existing positions (Coval and Stafford, 2007). Liquidation has a negative impact on the prices of the liquidated assets. The shock impacts indirectly also the value of other funds sharing assets with the shocked fund even though they are not initially hit by the shock. If these funds also experience a large loss as a consequence of liquidation by the shocked fund, it is possible that these funds have to liquidate part of their assets. In doing so, they cause a further drop in both the value of assets in common and the value of assets of all other holdings. Hence, the initial shock may trigger fire-sales spillover which propagates throughout the network of funds.

In what follows we formalize the mechanism of contagion propagation in the network. Let us consider a bipartite network with N_F funds investing in N_A assets. Let α_{ik} be the number of shares of asset k held by fund i. The market value MV_i of fund i is then given by

$$MV_i = \sum_{k=1}^{N_A} \alpha_{ik} P_k,$$

where P_k is the price of asset k. The drop in market value ΔMV_i for fund i due to a drop in the price ΔP_k for asset k, for $k = 1, \ldots, N_A$, is

$$\Delta MV_i = \sum_{k=1}^{N_A} \alpha_{ik} \Delta P_k. \tag{1}$$

Let $\psi(q, P)$ be the price-impact function such that

$$\frac{\Delta P}{P} = \psi(q, P) \tag{2}$$

where q is the liquidated volume for a given asset, P is the asset price before liquidation, and ΔP is the price loss from liquidation. By Equations (1) and (2), the loss of market value ΔMV_{ij} experienced by fund i when fund j liquidates a fraction ε_j of its holdings is[2]

$$\Delta MV_{ij} = \sum_{k=1}^{N_A} \alpha_{ik} P_k \psi(\alpha_{jk} \varepsilon_j, P_k). \tag{3}$$

Hence, the relative loss of market value for a fund i when any other fund j liquidates a fraction

[2]Common assets holdings are the main drivers of indirect contagion among financial institutions which are not exposed to counterparty risk (see Cont and Schaanning, 2019, and the references there). This is why we do not use realized assets' returns to compute the losses experienced by funds. In particular, we do not directly shock assets' returns which would propagate throughout the network by means of correlation. Rather, the model we used provides a mechanism of propagation of indirect contagion mediated by common assets holdings. It is worth noticing that indirect contagion may also affect assets which are not correlated with the ones that trigger the market value loss cascade at the beginning. A completely different approach would be to look at returns and their correlations. This approach would provide complementary information that cannot simply be added to that from common asset holdings. Moreover, it would not allow disentangling the contribution of indirect contagion from other possible sources.

ε_j of its assets is

$$Loss_i = \frac{1}{MV_i}\sum_{j=1}^{N_F}\sum_{k=1}^{N_A}\alpha_{ik}P_k\psi(\alpha_{jk}\varepsilon_j, P_k). \tag{4}$$

More generally, by denoting with I_g a set of indexes labeling funds in a particular group g, from Equation (4) we can obtain also the relative market value loss $Loss_g$ which is lost by all funds in that group due to liquidation from each fund in the network

$$Loss_g = \frac{1}{MV_g}\sum_{i\in I_g}\sum_{j=1}^{N_F}\sum_{k=1}^{N_A}\alpha_{ik}P_k\psi(\alpha_{jk}\varepsilon_j, P_k), \tag{5}$$

where $MV_g = \sum_{i\in I_g} MV_i$ is the total market value of all funds in the group g.

Notice that Equation (5) can be rewritten as

$$Loss_g = N_F\left[\frac{1}{N_F}\sum_{j=1}^{N_F}\left(\frac{1}{MV_g}\sum_{i\in I_g}\sum_{k=1}^{N_A}\alpha_{ik}P_k\psi(\alpha_{jk}\varepsilon_j, P_k)\right)\right], \tag{6}$$

where the term in round brackets is the relative total loss experienced by all funds belonging to group g when fund j liquidates a fraction ε_j of its assets. Hence, Equation (6) shows that the relative total loss for funds in group g obtained when all funds liquidate their portfolios simultaneously is proportional to the average relative total loss experienced by the funds in that group due to liquidation by one fund at a time.

We next specify the price-impact function in Equation (2). Since the seminal paper of Kyle (1985), the linear market-impact model has been widely used to study price impacts. We are aligned with this strand of literature, using it as a baseline approach for our analysis. For a robustness check of results, we also implement the non-linear model from Cont and Schaanning (2019) to simulate the deleveraging cascade in addition to the linear model.

2.1 Linear market-impact model

Following Cont and Schaanning (2019) and Braverman and Minca (2018), we assume a linear market-impact model (Kyle, 1985). Liquidation of q shares of asset k impacts its price P_k according to

$$\psi(q, P_k) = \frac{q}{\lambda_k}, \tag{7}$$

where λ_k measures the market depth for stock k. According to Amihud (2002) or Almgren et al. (2005), an empirical estimate of the market depth is provided by

$$\lambda_k = c \frac{ADTV_k}{\sigma_k} \tag{8}$$

where $ADTV_k$ is the Average Daily Trading Volume for asset k, σ_k is the standard deviation of the returns for asset k, and c is a suitable proportionality constant which is independent from the asset.

By using the model specification (7) in Equation (3), we obtain

$$\Delta MV_{ij} = \sum_{k=1}^{N_A} \alpha_{ik} \frac{P_k}{\lambda_k} \alpha_{jk} \varepsilon_j. \tag{9}$$

We define the generic (i, j) element of the funds adjacency matrix as

$$\Omega_{ij} = \sum_{k=1}^{N_A} \alpha_{ik} \frac{P_k}{\lambda_k} \alpha_{jk}. \tag{10}$$

The term Ω_{ij} measures the overlap between portfolios for funds i and j respectively and can be used to rewrite the market value loss given in Equation (9) as

$$\Delta MV_{ij} = \Omega_{ij} \varepsilon_j.$$

In the overlap between two portfolios, any asset in common is weighted by the inverse of its market depth λ. A more liquid asset (higher market depth) has a lower weight in the overlap. Indeed, a more liquid asset is less affected by liquidation; hence, its contribution to risk propagation is lower. The adjacency matrix is then used to compute the relative loss of market value for a fund i when any other fund j liquidates a fraction ε_j of its assets. Such a loss is

$$Loss_i = \frac{1}{MV_i} \sum_{j=1}^{N_F} \Omega_{ij} \varepsilon_j. \tag{11}$$

Finally, the relative total loss $Loss_g$ in (5) which is lost by all funds in a given category g due to liquidation from each fund in the network reads

$$Loss_g = \frac{1}{MV_g} \sum_{i \in I_g} \sum_{j=1}^{N_F} \Omega_{ij} \varepsilon_j. \tag{12}$$

We highlight that Equation (12) measures first-order losses and does not account for feedback effects. Indeed, liquidation by a given fund i impacts any other fund sharing with i a portion of its assets. In turn, if a second fund j is forced to liquidate part of its assets because of the market value loss caused by fund i, its action may cause a further drop in the market value of fund i. To account for one-loop feedback effect, after a first round of losses, portfolio weights and asset values have to be updated and a second round of losses has to be evaluated. The loss for a fund is then given by the sum of the losses in the two rounds.

Our identification strategy relies on a network analysis where funds are not taken as stand-alone entities but are interconnected components of a unified system. The proposed model is based on how the interplay of three elements determines the extent to which funds are more or less permeable to contagion: the assets in common with the other funds, the volatility of such assets, and their trading volumes. Such elements contribute to the computation under different viewpoints; hence, the answer is not trivial and adds a new perspective to the risk analysis of ESG investing. Reduction in stakeholder risk and longer-term strategies make the assets held by the *High* ESG ranked funds less volatile. Moreover, the *High* ESG ranked funds exploit a non-mainstream segment of the market, thus reducing their overlap with the other funds. These drivers lead to less contagion for the *High* ESG ranked funds. From a different perspective, non-mainstream assets imply also higher concentration risk for the *High* ESG ranked funds and lower trading volumes for the assets held in portfolio by the *High* ESG ranked funds, hence increasing the possibility of contagion among these funds.

Finally we notice that an endogeneity issue may arise when using asset trading volumes and volatilities to measure the impact of contagion among ESG funds. Indeed, *High* ESG ranked funds are more oriented towards best-in-class strategies with longer-term horizons, thus implying lower asset volatilities and trading volumes. However, while higher ESG scores may be endogenously related to lower asset volatilities and volumes, lower values for such variables do not automatically imply a lower market value loss – which is the final output of our analysis, as we show below. In this respect, the implemented analysis does not offer apparent sources of bias when computing losses from indirect contagion in ESG funds.

2.2 Non-linear market-impact model

As a further specification of the price-impact function (2), and with the purpose of providing a robustness check of the results of the linear model (see Section 3.3), we consider the following non-linear formulation

$$\psi(q,P)=\left(1-\frac{B}{P}\right)\left(1-e^{-\frac{q}{\lambda\left(1-\frac{B}{P}\right)}}\right) \tag{13}$$

where λ is the asset market depth and B is a floor for the asset price P. The linear model given in (7) is suitable for matching the observed price impact for small volumes q. The non-linear model in (13) is proposed in Cont and Schaanning (2019) as a further specification to compute the price impact for large volumes during the fire-sales cascade. Moreover, it matches the price impact from the linear function (7) for small volumes q. The floor prevents the asset price from falling below B. This feature of the model accounts for the arrival of buy orders from large institutional value-investors when prices drop far below fundamentals.

3 Empirical analysis

For each quarter from the last day of March 2016 to the last day of June 2018, we construct a bipartite network containing equity mutual funds characterized by different levels of compliance with ESG aspects. First, we focus on the top 20% (*High* ESG ranked) and bottom 20% (*Low* ESG ranked) funds and describe their main characteristics, also in relation to the whole network.[3] Then we compare the relative total loss of market value due to portfolio liquidation experienced by the *High* ESG ranked funds with that for the *Low* ESG ranked funds. In particular, we test through the linear market-impact model in Section 2.1 whether the relative total loss for the *High* ESG ranked funds is different from that of the *Low* ESG ranked funds. As robustness checks, we further verify the validity of the considered research question when (1) we control for size, (2) we consider the top (bottom) 10% funds as the *High* (*Low*) ESG ranked funds, (3) market value loss from fire sales is corrected by a further term that accounts for a one-loop feedback effect in contagion propagation, and (4) the non-linear market-impact model presented in Section 2.2 is implemented.

[3]A more conservative categorization of funds – where the *High* (*Low*) ESG ranked funds are those in the top (bottom) 10% of the ESG score distribution – is considered in Section 3.3 on robustness.

3.1 Dataset description

Data at the fund-share-class level are retrieved from Morningstar Direct (MD) that also provides our main variable of interest, namely the Morningstar Historical Sustainability Score. Mutual-fund-share-class-level observations are aggregated at the fund level using the unique fund identifier ($FundId$) in MD (Patel and Sarkissian, 2017). The resulting sample consists of $12,536$ unique open-ended equity mutual funds rated on ESG aspects investing, globally or in a specific macro-geographic region/country, in $53,711$ assets. We match Morningstar Direct funds with the Morningstar European Data Warehouse (EDW) to retrieve at the portfolio-holdings level all the information related to fund-portfolio constituencies.

To such a unique sample of funds and their characteristics, we apply the following cleaning criteria. First, funds whose capitalization measured by the fund's Total Net Asset (TNA) is not available are eliminated. As a further step, we keep in the sample only funds for which we have holdings information for at least the 80% of portfolio capitalization. Funds whose holdings exceed 100% are also eliminated. Finally, we eliminate from the sample those funds that are too small in terms of TNA or in terms of the number of assets in portfolio, thus ensuring a minimum level of internal diversification for the funds in the dataset.[4]

Asset prices and trading volumes at the firm level are taken from Refinitiv (DATASTREAM). For each cross-section, we keep only assets whose historical series of daily returns and daily trading volumes are available for the past year. Portfolio holdings are then normalized to one for each fund in the sample.

We rank funds for ESG according to the Morningstar Historical Portfolio Sustainability Score released by Morningstar since 2016. For each point in time, such a score is computed as a weighted average of the Portfolio Sustainability Score over the past 12 months and ranges from 0 to 100. The Portfolio Sustainability Score is an asset-weighted average of the Sustainalytics' company-level rating.[5] To receive a Portfolio Sustainability Score, at least 67% of the assets under manage-

[4]The funds eliminated are those whose TNA is lower than the 2.5-th percentile of the cross-sectional TNA distribution or those investing in less than the 2.5-th percentile of the distribution of the number of assets in the cross-section. Then the remaining funds have at least a capitalization of 100,000 USD and invest at least in 14 assets.

[5]Since 2019, Morningstar changed its methodology by replacing Sustainalitics' company ESG rating with an ESG Risk rating. Starting from the Historical Portfolio Sustainability Score, Morningstar also provides the Globe rating system, which classify funds in 5 different ESG categories. However, the Morningstar Globe is not a time-series datatype, unlike the Historical Portfolio Sustainability Score.

ment in the fund must have a company ESG score.[6]

The number of unique funds N_F and the number of unique assets N_A of the estimation sample for each cross-section are shown in Table I. The table also reports the number of unique funds N_F^{ranked} that received a Historical Portfolio Sustainability Score by Morningstar, and the number of unique assets $N_A^{High\ ranked}$ and $N_A^{Low\ ranked}$ in which the *High* and the *Low* ESG ranked funds invest respectively.

Table I. Estimation sample across different cross-sections

The table shows the number of unique funds N_F and the number of unique assets N_A globally held by funds for each cross-section. The table also reports the number of unique ESG ranked funds N_F^{ranked} and the number of unique assets $N_A^{High\ ranked}$ and $N_A^{Low\ ranked}$ in which the *High* and the *Low* ESG ranked funds invest respectively.

	Mar-16	**June-16**	**Sep-16**	**Dec-16**	**Mar-17**	**June-17**	**Sep-17**	**Dec-17**	**Mar-18**	**June-18**
N_F	6,044	6,304	6,313	5,568	5,612	5,828	5,819	5,999	5,754	5,778
N_A	17,996	18,272	18,562	18,406	18,702	17,928	18,201	19,507	19,789	20,040
N_F^{ranked}	790	857	865	784	784	809	862	5023	4934	5234
$N_A^{High\ ranked}$	1,485	1,737	1,726	1,672	1,726	1,676	1,838	6,948	7,053	7,283
$N_A^{Low\ ranked}$	3,582	7,187	7,299	7,231	7,151	6,428	6,690	12,255	12,586	14,400

The number of ranked funds ranges from 790 in the first quarter of 2016 to 5,234 in the second quarter of 2018. The low numbers of ranked funds in the first quarters is an indication that there can be ESG funds which are not ranked for those cross-sections.[7] Consistent with our research question on how *High* and *Low* ESG ranked funds react to fire-sales spillover propagating throughout the network, we focus here on only these two groups of funds.[8] Not surprisingly, the last two rows in Table I show that the *High* ESG ranked funds invest in a much smaller subset of assets than the *Low* ESG ranked category. Indeed, to be high ranked, the former have to tilt their

[6]The threshold of 67% is also used in El Ghoul and Karoui (2017), who construct their own ESG fund score.

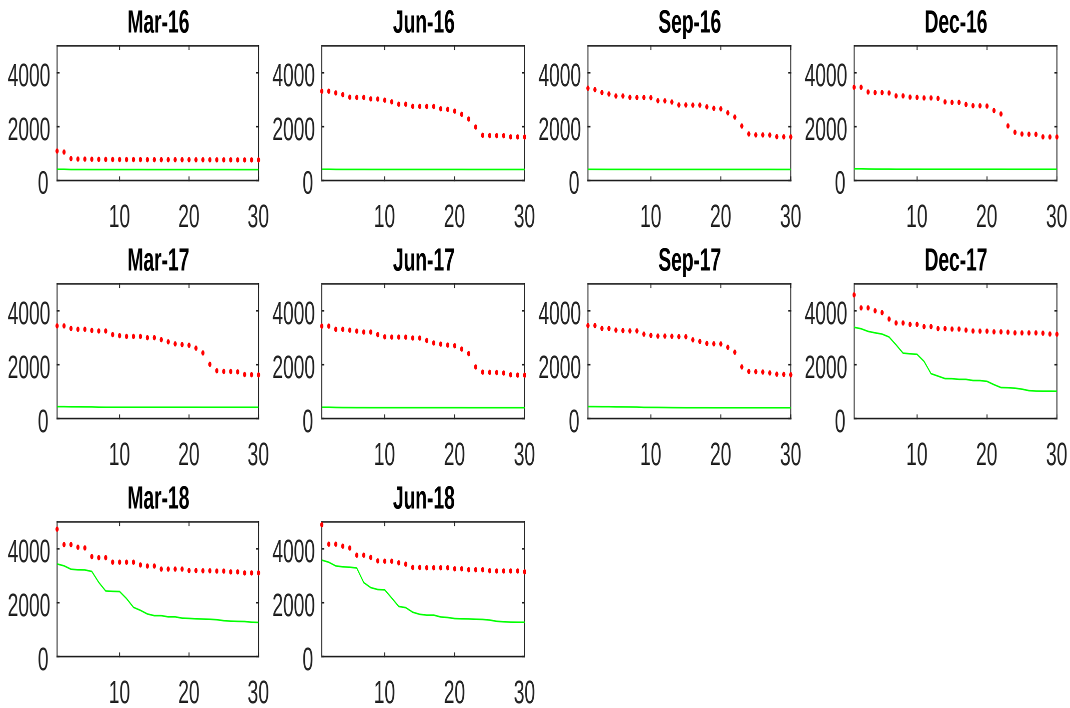
[7]This is a limitation of ESG data when dealing with ranked funds in past years.

[8]In Appendix A, we provide the main descriptive statistics for the relevant variables related to the entire network of funds (see Table A-I). The average fund appears to be well diversified (Panel A). The degree of diversification is confirmed by its Herfindahl-Hirschman index, which is always near the lower bound (Panel B). It manages around 200 million USD (Panel C) and achieves an average daily return of about 0.03% (Panel D) with an average standard deviation of 1.0% (Panel E).

portfolio towards the best-performing assets in the ESG dimensions.

We first consider the degree of overlap of the funds in the network. Figure I shows the 30 highest portfolio overlaps in terms of the number of assets that the *High* ESG ranked funds (solid lines) and the *Low* ESG ranked ones (dotted lines) have in common with all the funds in the network (out-of-class and intra-class overlap). The *High* ESG ranked funds share with all funds

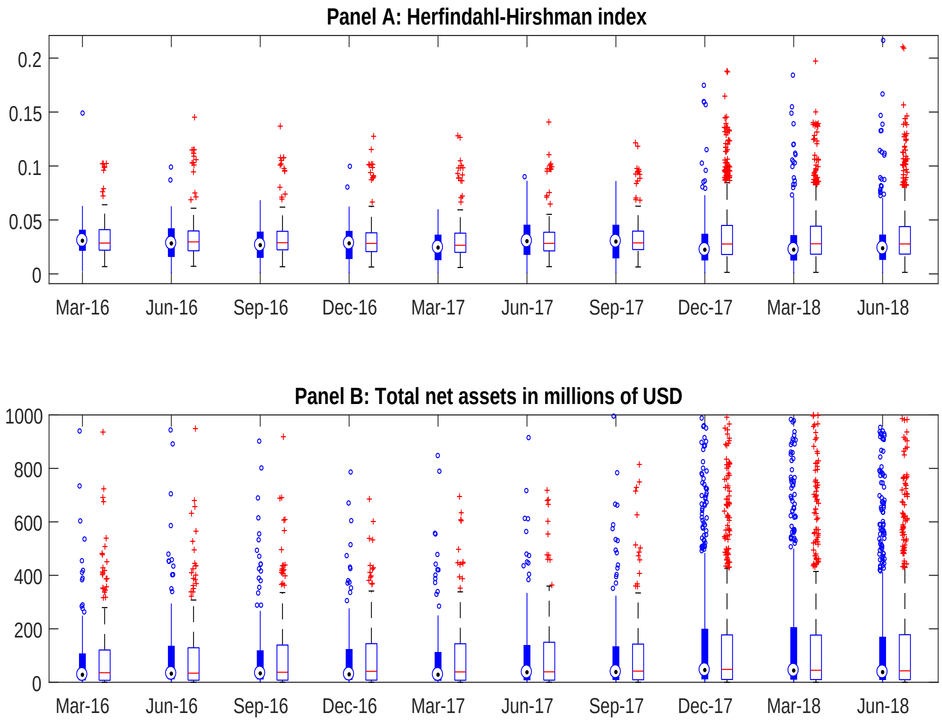
Figure I. Portfolio overlaps.



The figure shows the 30 highest (x-axis) portfolio overlaps in terms of the number of assets in common (y-axis) for the *High* ESG ranked funds (solid line) and the *Low* ESG ranked funds (dotted line) with all the funds in the network (out-of-class and intra-class overlap). Subplots refer to the last day of each quarter.

in the network the lowest number of assets. For example, in June 2018, the first 30 overlaps of the *High* ESG ranked funds with all funds range from 3,582 to 1,274 assets, while the overlaps of the *Low* ESG ranked funds with all funds vary from 4,896 to 3,147 assets. In March 2016 the first 30 overlaps range from 405 to 418 assets for the *High* ESG ranked funds and from 765 to 1,095 assets for the *Low* ESG ranked funds. The lower overlaps in the 2016–2017 cross-sections are due to the smaller sets of funds that are *High* or *Low* ESG ranked. In general, for each cross-section, the *Low* ESG ranked funds share with all the funds in the network a higher number of assets than the *High* ESG ranked funds. This is because by tilting their portfolios towards the assets with higher ESG performance, the *High* ESG ranked funds shift their opportunity set toward a segment of the market that is not generally exploited by funds.

Figure II. Funds concentration and capitalization.

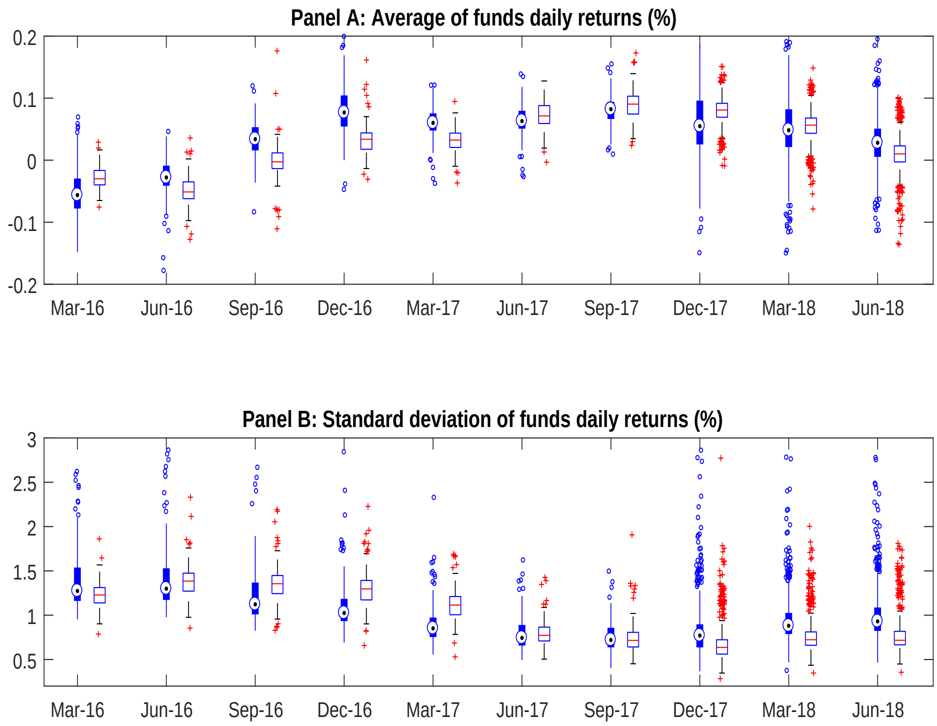


The figure shows a cross-sectional boxplot of the funds' Herfindahl-Hirschman index distribution (Panel A) and the funds' capitalization in millions of USD (Panel B), for the *Low* ESG ranked funds (filled boxes) and the *High* ESG ranked funds (empty boxes) for each cross-section in the sample. Labels on the x-axis refer to the last day of each quarter.

Figures II and III provide a *High*-versus-*Low* comparison of the funds distributions of some relevant variables across the different time points analyzed. Figure II (Panel A) shows a boxplot of the funds' Herfindahl-Hirschman index built from portfolio weights for the *Low* ESG ranked funds (filled boxes) and the *High* ESG ranked funds (empty boxes). The concentration Herfindahl-Hirschman index ranges from 0 (low concentration) to 1 (high concentration). Funds are always well diversified, with a concentration index assuming values close to the lower bound of the interval for each quarter. Figure II (Panel B) is a boxplot of the funds capitalization (in millions of USD). Distributions of funds capitalization are leptokurtik and positively skewed. Figure II shows no substantial difference either in portfolio concentration or in the funds capitalization among the *High* and *Low* ESG ranked funds distributions.

Figure III shows a boxplot of the average (Panel A) and the standard deviation (Panel B) of the daily returns of the *Low* ESG ranked funds (filled boxes) and the *High* ESG ranked funds

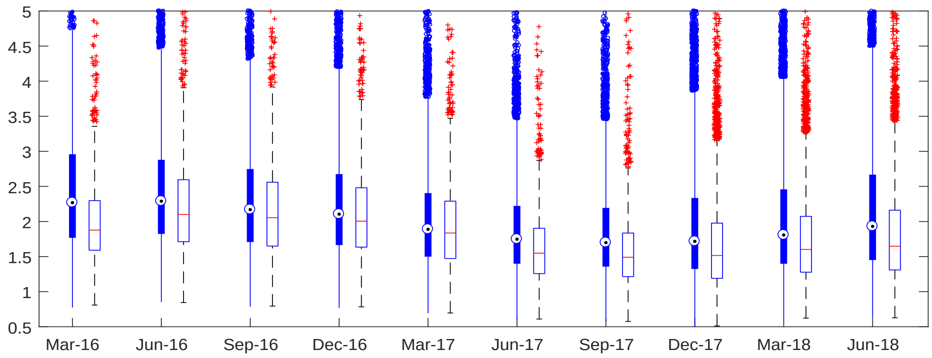
Figure III. Funds average and standard deviation of daily returns.



The figure shows a cross-sectional boxplot of the average (Panel A) and the standard deviation (Panel B) of the daily percentage returns for the *Low* ESG ranked funds (filled boxes) and the *High* ESG ranked funds (empty boxes) for each cross-section. Labels on the x-axis refer to the last day of each quarter, and the averages and standard deviations are estimated considering a one-year window of past daily observations.

(empty boxes) across different points in time. For each quarter t, the averages and the standard deviations are computed considering one year of daily data up to quarter t. Figure III shows that the cross-section distributions are more disperse for the *Low* ESG ranked funds. Mixed evidence emerges from Figure III concerning the the risk/return profile of ESG funds. Consistent with Hong and Kacperczyk (2009) and the *responsibility effect* documented by Becchetti et al. (2018), *High* ESG ranked funds are less remunerative (Panel A) than the *Low* ESG ranked ones in June, September, and December 2016, March 2017, and June 2018. In March 2016 and December 2017, the boxplots for the *Low* ESG ranked funds present a lower median value than the *High* ESG ranked funds, but they show also greater dispersion. In the remaining cross-sections, the distributions are comparable. Typically, the *High* ESG ranked funds are also less risky (Panel B) than their *Low* ESG ranked counterparts. The higher risk for *Low* ESG ranked funds could be justified by their higher exposition to stakeholder risk (Becchetti et al., 2018), crash risk (Kim et al., 2014, Boubaker et al., 2020), market risk (Albuquerque et al., 2019), or to a combination of these sources of risk. In September and December 2016, and in March 2017, we observe an opposite behavior of the *High* ESG ranked funds distributions more tilted towards higher values than the distributions for the *Low* ESG ranked funds.

Figure IV. Standard deviation of assets daily returns.



The figure shows a cross-sectional boxplot of the volatility distributions of the assets in which *Low* ESG ranked funds (filled boxes) and *High* ESG ranked funds (empty boxes) invest for each cross-section. Labels on the x-axis refer to the last day of each quarter, and volatilities are estimated using a one-year window of past daily observations. The vertical axis is expressed in percentages and is cut off at 5% in order to ease visualization of the data.

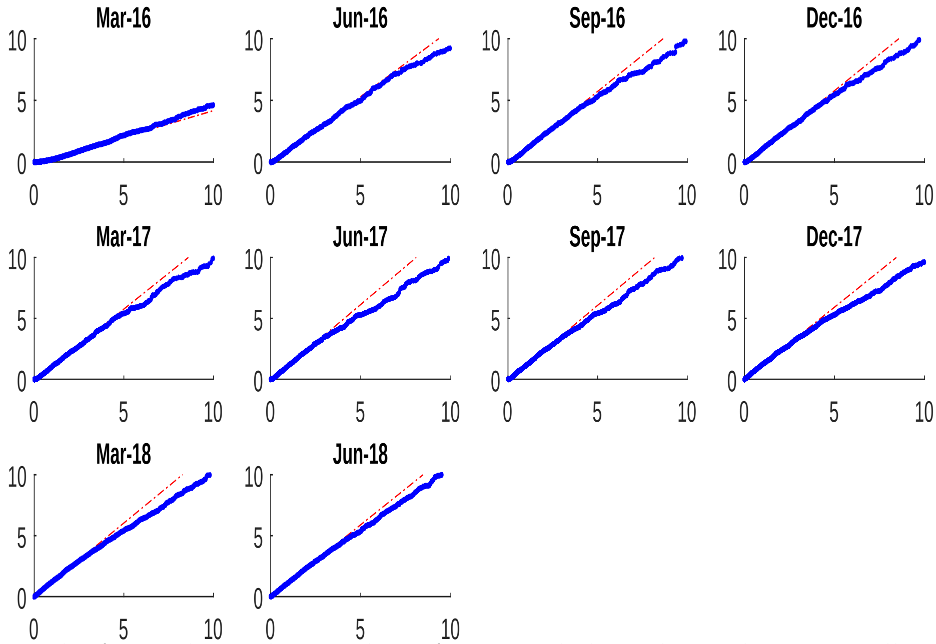
Figure IV compares the volatility distributions of the assets in which *Low* ESG ranked funds (filled boxes) and *High* ESG ranked funds (empty boxes) invest. The figure shows that assets in the investment universe of the *High* ESG ranked funds are less risky than assets in the investment set of the *Low* ESG ranked funds. That we observe a different behavior for funds volatility (Figure III, Panel B) in some cross-sections at the end of 2016 is due to correlations among assets.

Figure V shows the q-q plots of average daily trading volume of the assets in which *High* ESG ranked funds (y-axis) and *Low* ESG ranked funds (x-axis) invest. For each cross-section analyzed, the average is computed by considering daily observations of the number of shares traded over the past year. Figures for volumes are in millions of traded shares. For each cross-section, except that of end of March 2016, trading-volume distributions for assets held by *Low* ESG ranked funds are tilted more towards larger values than assets in the *High* ESG ranked portfolios.

3.2 Network analysis

For each quarter from the last day of March 2016 to the last day of June 2018, we consider a bipartite network consisting of N_F funds that invest globally in N_A assets as reported in Table I. We first implement the linear price impact function as in Equation (7).

Figure V. Assets average daily trading volume.

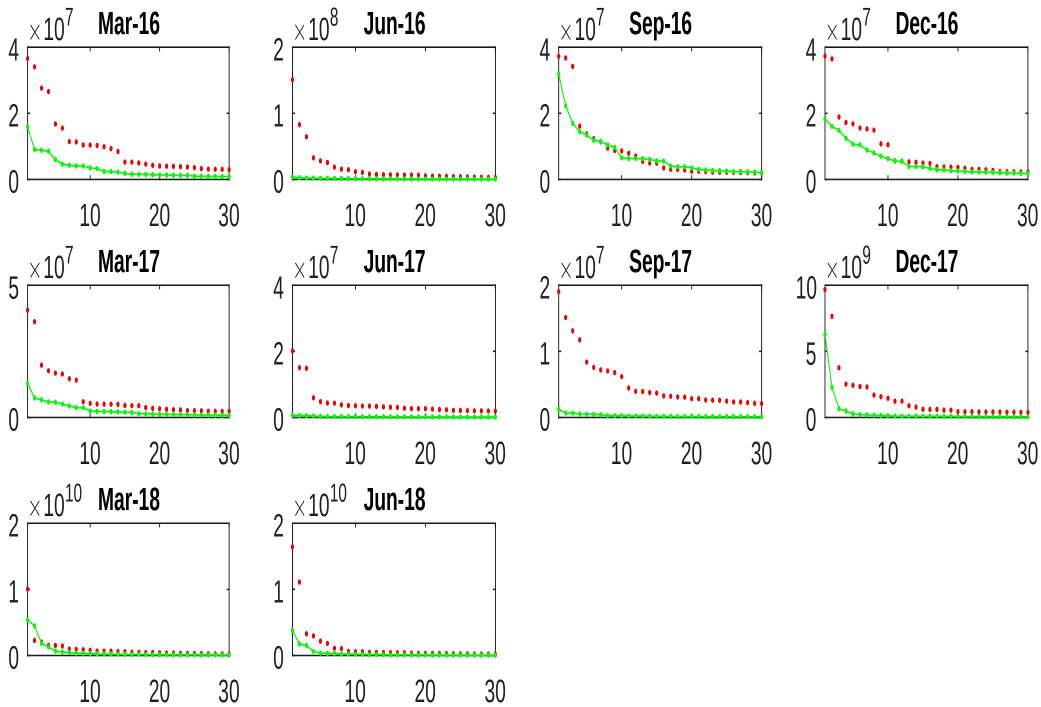


The figure shows the q-q plots of average daily trading volume (in millions of shares traded) of the assets in which *High* ESG ranked funds (y-axis) and *Low* ESG ranked funds (x-axis) invest. Subplots refer to the last day of each quarter. For each cross-section analyzed, the average is estimated using a one-year window of past daily observations. Each subplot compares the quantiles of the average daily trading volume distributions for the two categories. The dashed straight line represents the case when the two distributions have the same quantiles. If the scatterplot of the quantiles (thick blue line) is below the dashed line, the distribution represented in the x-axis (*Low* ESG ranked funds) is more tilted towards higher values than the distribution reported in the y-axis (*High* ESG ranked funds).

Following Cont and Schaanning (2019), we calibrate the linear market-impact model in Section 2.1 by imposing that the median loss value for the assets in the sample is 440 bsp for 10 billion USD liquidated. This provides an estimate of c. Other proposals of calibration are given, for example, in Cont and Wagalath (2016) and Ellul et al. (2011).

Lower asset volatilities (Figure IV) and lower trading volumes (Figure V) for the assets held by the *High* ESG ranked portfolios provide a market depth, as defined in Equation (8), that can be either higher or lower than the market depth of the constituencies of the *Low* ESG ranked funds. Since the effective overlap between two funds, as given in Equation (10), is obtained by weighting the shared holdings by their asset market depth, such characteristic may either increase or reduce portfolio overlap, thus either strengthening or weakening the connections responsible for risk propagation.

Figure VI. Liquidity weighted portfolio overlaps.



The figure compares the highest 30 (x-axis) portfolio overlaps (y-axis), computed according to Equation (10), of the *High* ESG ranked funds (solid line) and of the *Low* ESG ranked funds (dotted line) with all funds in the network (intra-class and out-of-class overlap). Subplots refer to the last day of each quarter.

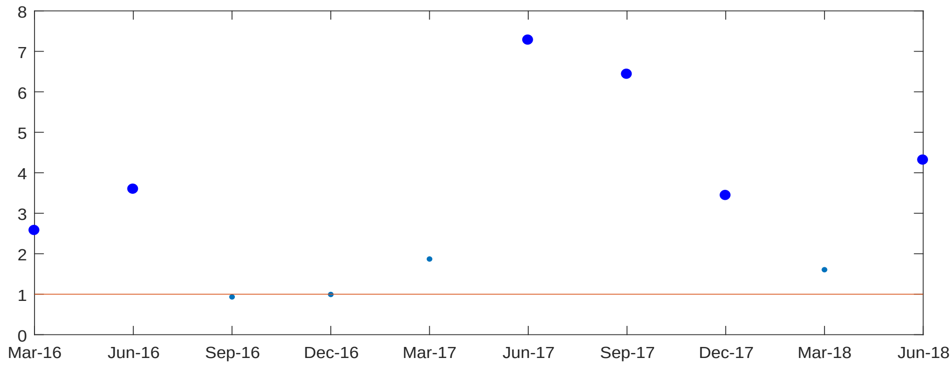
Similar to Figure I, in Figure VI the 30 highest liquidity weighted overlaps of the *High* ESG ranked funds with all the funds in the network are compared with the 30 highest overlaps of the *Low* ESG ranked funds with all the funds in the network (intra-class and out-of-class overlap).

After liquidity adjustment, the *High* ESG ranked funds still show lower overlaps than the *Low* ESG ranked ones in eight out of 10 cross-sections. In the remaining two (September 2016 and March 2018), liquidity weighting smooths the dominance of one class over the other.

Figure VII shows the ratio of the relative total loss of market value as given in Equation (12) for the *Low* ESG ranked funds over the relative total loss for the *High* ESG ranked funds when all funds in the network liquidate 1% of their assets. Note that the loss ratio does not depend on the value of the calibrated constant c for the linear model specification.[9] This ratio is always greater than one (horizontal line), with the exception of the cross-sections relative to September and December 2016, when the ratio is 0.93 and 0.99 respectively. For these two cross-sections,

[9]In a linear model, this ratio is also independent from the fraction of assets liquidated.

Figure VII. Relative total loss ratio.



Ratio of the relative total loss of market value for the *Low* (bottom 20%) ESG ranked funds compared with the *High* (top 20%) ESG ranked funds. The cases represented by bigger dots are those for which the difference in average losses is significant at the 5% level. Labels on the x-axis refer to the last day of each quarter.

we already observed a higher volatility of *High* ESG ranked funds returns (see Figure III, Panel B). Hence, the relative total loss experienced by the *Low* ESG ranked funds in case of fire-sales spillover is larger than that for the *High* ESG ranked funds in eight out of 10 cross-sections.

We then test the alternative hypothesis that the difference of the relative total loss experienced by the two groups is statistically different from zero against the null hypothesis that such a difference is zero.[10] The cases where the difference is significant at the 5% level are represented by bigger dots in Figure VII. Results are significant for six out of 10 cross-sections. For all the significant cases, this difference is positive, meaning that the loss for the *High* ESG ranked funds is significantly lower than the loss for the *Low* ESG ranked funds.

Remarkably, the different time frames considered are characterized by different volatility regimes. Table A-II in the Appendix compares average returns and standard deviations of the MSCI World Index and the MSCI World ESG Index computed for each cross-section on the past year daily data. Table A-II shows that the 2016 quarters are periods of higher volatility with negative average returns in the first two quarters. Results for the latter, characterized by a certain degree of negative downturn, confirm our general findings. In the last two quarters of 2016, the loss for the *Low* ESG ranked funds is instead slightly lower than that for the *High* ESG ranked funds. However, the result in these cases is not significant.

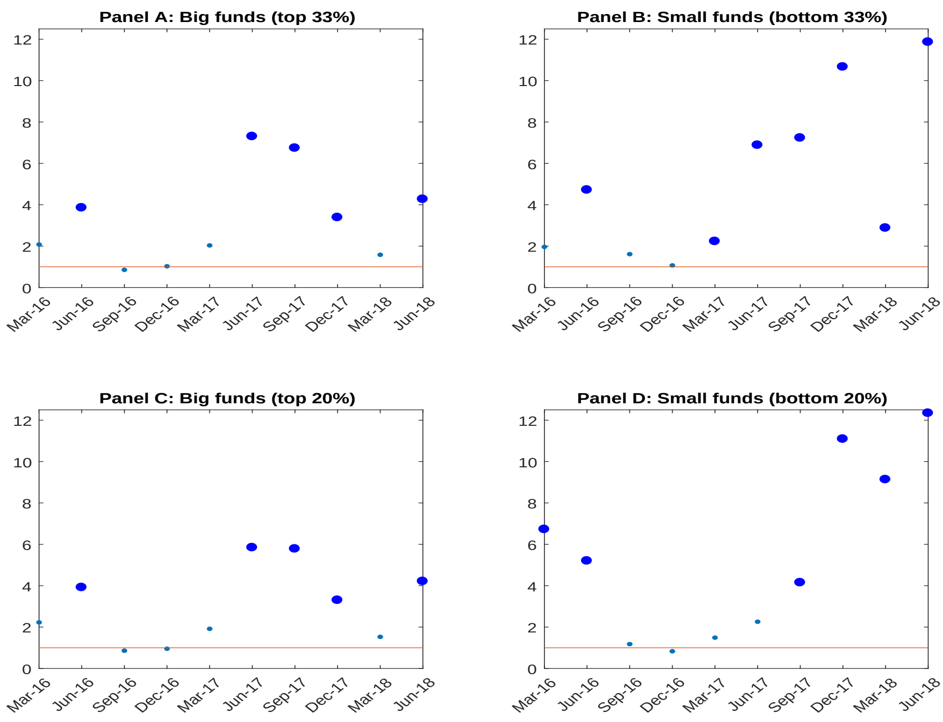
[10]As shown in Equation (6), the relative total loss for the *High* (*Low*) ESG ranked funds is proportional to the average over all funds in the network of the relative total loss experienced by the *High* (*Low*) ESG ranked funds due to liquidation by one fund at a time. Hence, a standard t-test can be performed.

3.3 Robustness

To check whether our findings are robust, we first control results for different size cutoffs. Then, we adopt a more conservative classification of the *High* and *Low* ranked funds as those in the top and bottom 10% of the ESG Historical Sustainability Score distribution. As a third check, we also consider a one-loop feedback contribution to the baseline result of Figure VII to account also for the loss coming from a second round of sales. Finally, we show results when the non-linear price-impact function in (13) is implemented.

For the specific case of size, we consider two different cutoffs: top/bottom 33% and top/bottom 20% of the fund-size distributions. Figure VIII, Panel A reports the ratio of the losses of the *Low*

Figure VIII. Relative total loss ratio: robustness for size.

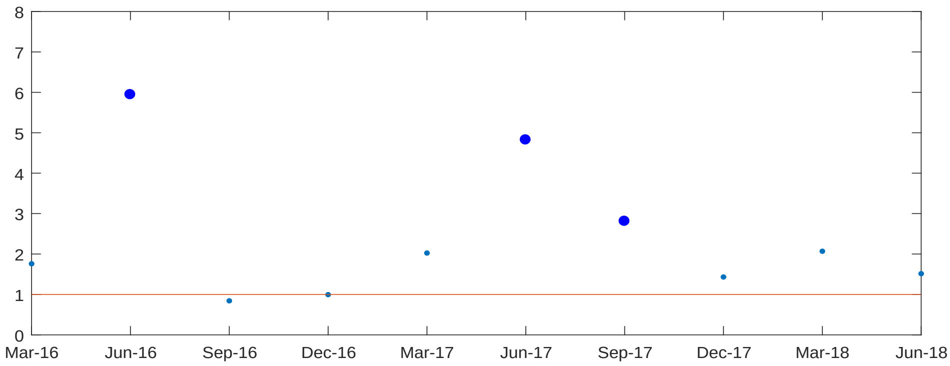


Ratio of the relative total loss of market value for the *Low* ESG ranked funds with respect to the *High* ESG ranked funds for different fund sizes. Panel A (B) shows results for the funds in the top (bottom) 33% of the fund-size distribution. Panel C (D) shows results for the funds in the top (bottom) 20% of fund-size distribution. In all cases the relative total loss is computed as a response to liquidation from the whole network. The cases represented by bigger dots are those for which the difference in average losses is significant at the 5% level. Labels on the x-axis refer to the last day of each quarter.

ESG ranked / *Big 33%* funds with respect to the *High* ESG ranked / *Big 33%* funds in response to fire sales from all funds in the network. Panel B reports the same ratio for the *Small 33%* funds. Panels C and D show the loss ratio for the two ESG categories for the *Big 20%* and *Small 20%*

funds respectively. *Big* and *Small* funds confirm our main results for both size cutoffs. Specifically, results for *Big* funds (Panel A and Panel C) mainly replicate those reported in Figure VII. In the small funds case, we observe even an amplification of the ratio of losses between the *High* ESG ranked and the *Low* ESG ranked funds (Panel B and Panel D).

Figure IX. Relative total loss ratio: robustness for ESG ranking cutoff.



Ratio of the relative total loss of market value for the bottom 10% ESG ranked funds with respect to the top 10% ESG ranked funds. The cases represented by bigger dots are those for which the difference in average losses is significant at the 5% level. Labels on the x-axis refer to the last day of each quarter.

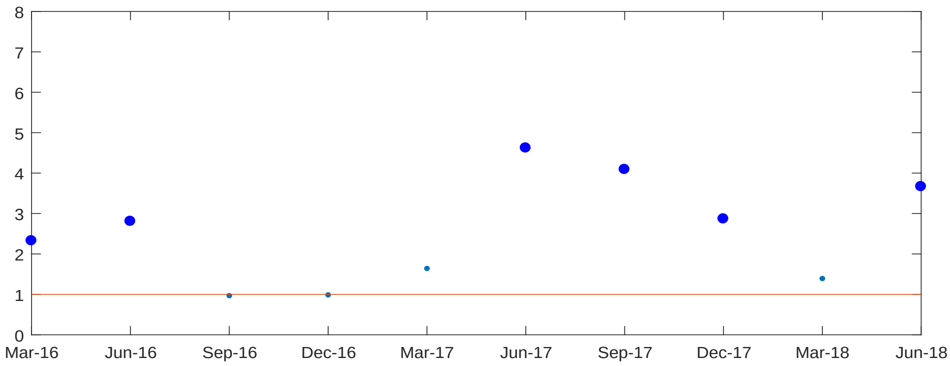
Concerning the second robustness check, we compare the losses of the top (bottom) 10% ESG ranked funds. Results in Figure IX confirm the general findings of our baseline analysis, lower losses of the *High* ESG ranked funds in the same eight out of 10 cross-sections. However, results are significant for only three cases out of 10.

Feedback contribution is accounted for in Figure X. The figure confirms our main results showing that the ratio of the market value losses for the two ESG ranked categories remains stable due to a partial compensation for such a contribution among the two groups of funds.

Finally, we check whether the results are robust when using the non-linear price-impact function given in Equation (13). We follow Cont and Schaanning (2019) for calibration. First, B is fixed for each stock at 50% of the asset price. Then, c is calibrated in the same manner as in the linear case, by imposing that the median loss value for the assets in the sample is 440 bsp for 10 billion USD liquidated. Unlike the linear case, the ratio of losses in this case is sensitive to calibration. Hence, we also test the sensitivity of results to calibration by considering a median loss value equal to 50 bsp and 2,000 bsp for 10 billion USD liquidated.

Results for the loss ratio are reported in Figure XI for each cross-section, where the different

Figure X. Relative total loss ratio with feedback.



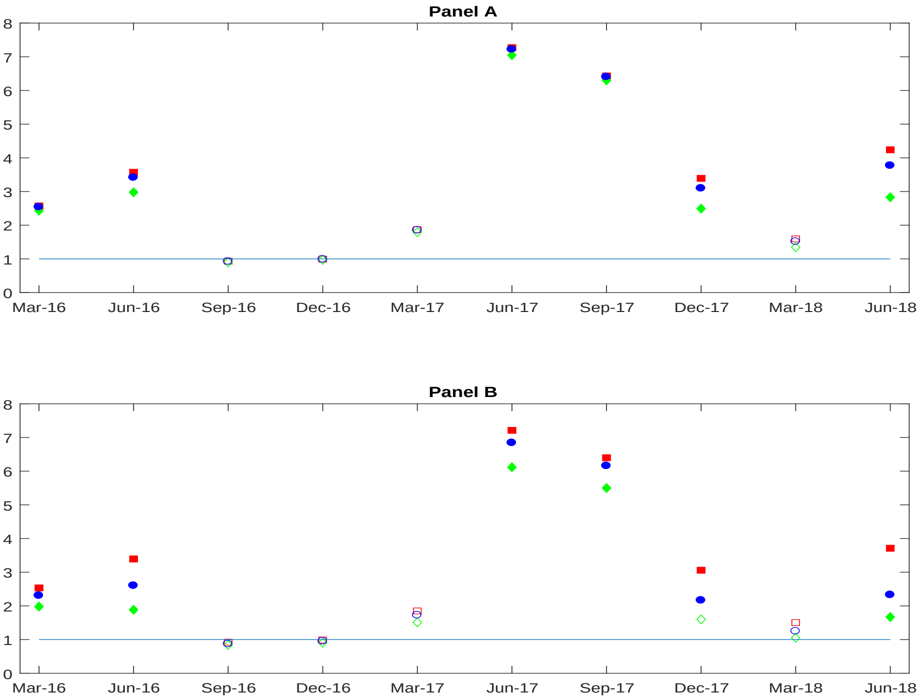
Ratio of the relative total loss of market value for the *Low* ranked funds (bottom 20%) with respect to the *High* ranked ones (top 20%) when the feedback affect is accounted for. The cases represented by bigger dots are those for which the difference in average losses is significant at the 5% level. Labels on the x-axis refer to the last day of each quarter.

calibration settings are represented by blue circles (red squares and green diamonds) corresponding to a median loss value for the assets in the sample equal to 440 bsp (50 bsp and 2,000 bsp, respectively) for 10 billion USD liquidated. Significant results are shown using filled markers. Panel A shows the case when the fraction of liquidated assets is 1%. Panel B reports results when 10% of the assets are liquidated. Since the model in Equation (13) depends also on a second parameter B, we also tested the model for different values of this parameter. Among them, we considered the case without a floor, i.e. $B = 0$. Results are quite similar to those presented here, and we do not report them since they add no additional insight. Findings emerging from Figure XI by implementing the non-linear model (13) are consistent with those discussed in the case where the linear model (7) is used.

4 Conclusions

Assets under management subject to ESG screening criteria have increased remarkably over time. This pattern could be the result of favorable risk/return characteristics offered by ESG investments, or of investors' taste for such assets. Since the 2008 financial crisis, measuring the impact of contagion on financial markets is one of the main concerns among policymakers. This paper is a first attempt to propose a network model for ESG funds and to present a systemic risk perspective by analyzing how funds with different levels of ESG compliance react to the contagion risk generated by fire sales on assets held in common by funds.

Figure XI. Relative total loss ratio for the non-linear model.



Ratio of the relative total loss of market value for the *Low* ESG ranked funds (bottom 20%) with respect to the *High* ESG ranked ones (top 20%) when the non-linear model in Equation (13) is used with B set for each stock to 50% of the asset price. Blue circles (red squares and green diamonds) correspond to the calibration where the median loss value for the assets in the sample is 440 bsp (50 bsp and 2,000 bsp, respectively) for 10 billion USD liquidated. Panel A shows results when the fraction of liquidated assets in Equation (5) is $\varepsilon = 1\%$. Panel B reports results when $\varepsilon = 10\%$. The cases represented by filled markers are those for which the difference in average losses is significant at the 5% level. Labels on the x-axis refer to the last day of each quarter.

To this aim, we match different datasets containing specific information at both the fund and holding levels to measure the magnitude of the interconnectedness of funds characterized by different ESG ratings. The overlap between portfolios defines the interrelation of funds in terms of common securities, weighted by the inverse of their market depth. Consequently, contagion from one fund to another is mediated by the overlap among the two portfolios.

We examine a network of funds engaging different levels of ESG. Specifically, we consider the network quarterly along a two-year period (March 2016–June 2018) characterized by different levels of asset volatility. In particular, 2016 is a period with higher volatility than the rest of the time span. We measure the market value that is lost by the funds because of fire-sales spillover. Results show that the loss is lower and statistically significant for the *High* ESG ranked funds in most of the cross-sections analyzed. In September and December 2016, the loss is slightly lower for the *Low* ESG ranked funds, but the difference with the *High* ESG ranked ones is not significant.

These results are robust to different sample and model specifications.

Our results indicate that contagion is less effective among funds achieving high ESG performance in periods with lower asset volatility. In periods of higher asset volatility, we did not observe a clear dominance of *High* ESG ranked funds over the other class of funds. A possible explanation is that *High* ESG ranked funds, while tilting their portfolios towards firms with high ESG score, are pursuing best-in-class strategies involving greater concentration risk that emerges during periods characterized by higher volatility.

Results are encouraging, but further investigation should be conducted to deeply analyze whether investments with a higher level of ESG compliance are more resilient to contagion risk in cases of financial distress. Indeed, in 2016 and in the first three quarters of 2017, only a few funds are ranked. Thus, there can be funds engaged in ESG which are not ranked. This is a well-known limitation flawing studies on ESG. Despite this limitation, we believe that our results provide insights for both asset managers and policymakers. The former can reach an enhanced portfolio diversification at both the macro and micro levels, by tilting their portfolio towards assets with higher ESG scores. The latter can improve the stability of the system by dissecting the interconnection among ESG funds to highlight the strength of the system to mitigate the effects of possible fire-sales spillover.

The network approach proposed allows relating a single fund choice to the rest of the market in order to fully include the long-term goal of ESG investing, this is the sustainability of the economy including the financial markets and their listed securities. Finally, this approach allows us to look at ESG investing as an integrated strategy where funds are interconnected in a complex network of mutually interacting nodes. In this way, both asset managers and policymakers might exploit the aggregate effect of portfolio diversification related to the system as a whole.

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Table A-I. Descriptive Statistics at Fund-level Across all Funds

The table reports funds descriptive statistics for all funds: the number of assets (Panel A), the Herfindahl-Hirschman index (Panel B), Total Net Assets in millions of USD (Panel C), past-year average daily returns in percentage (Panel D), and past-year standard deviation of daily returns as a percentage (Panel E).

	Mar-16	June-16	Sep-16	Dec-16	Mar-17	June-17	Sep-17	Dec-17	Mar-18	June-18
						Number of Assets - Panel A				
Min	18	19	19	19	20	16	14	15	14	15
Max	2,226	3,690	3,721	3,748	3,731	3,708	3,732	9,109	9,452	9,701
Mean	101.95	113.84	117.58	119.65	120.31	112.34	116.52	161.11	164.12	164.92
StdDev	181.70	243.19	252.91	265.12	267.75	254.82	256.01	424.28	438.64	442.66
Skewness	6.32	8.48	8.11	8.05	7.98	8.48	8.26	9.59	9.52	9.35
Kurtosis	56.41	98.97	90.01	87.13	84.49	95.44	92.09	135.14	133.46	130.39
						Herfindahl-Hirschman index - Panel B				
Min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Max	0.15	0.15	0.14	0.13	0.13	0.14	0.12	0.27	0.24	0.27
Mean	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03
StdDev	0.01	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
Skewness	1.66	1.99	1.75	1.76	1.95	1.67	1.51	2.45	2.15	2.45
Kurtosis	10.88	11.13	9.78	8.97	10.31	8.31	7.34	15.80	13.48	17.23
						Total Net Assets (millions of USD) - Panel C				
Min	0.12	0.10	0.10	0.11	0.10	0.11	0.10	0.11	0.10	0.10
Max	7,532.50	7,861.50	8,393.10	8,779.40	9,798.00	10,522.40	11,534.40	140,591.30	129,325.10	125,168.20
Mean	177.71	185.47	189.95	172.33	181.69	189.41	199.99	488.31	473.38	446.41
StdDev	524.04	543.55	565.09	525.06	566.04	589.96	688.04	3,348.58	2,793.87	2,581.98
Skewness	7.92	7.77	8.10	9.53	10.08	10.38	10.73	28.43	26.01	26.63
Kurtosis	84.32	81.91	88.43	125.99	139.99	149.09	147.31	1,050.73	1,014.19	1,106.63
						Average daily returns (%) - Panel D				
Min	-0.41	-0.39	-0.32	-0.05	-0.08	-0.23	-0.22	-0.21	-0.44	-0.46
Max	0.23	0.25	0.23	0.29	0.12	0.14	0.17	0.60	1.40	1.30
Mean	-0.03	-0.03	0.02	0.06	0.05	0.06	0.08	0.07	0.05	0.02
StdDev	0.04	0.04	0.04	0.04	0.03	0.03	0.03	0.04	0.05	0.04
Skewness	-1.22	1.42	0.27	1.61	-0.37	-1.98	-1.82	0.14	9.99	9.75
Kurtosis	21.39	23.06	16.96	7.96	4.88	15.91	19.83	12.72	276.79	289.02
						Average standard deviation of daily returns (%) - Panel E				
Min	0.00	0.00	0.00	0.00	0.00	0.00	0.32	0.28	0.00	0.12
Max	5.86	5.86	5.84	2.84	2.56	4.56	4.55	12.26	20.46	20.46
Mean	1.24	1.32	1.21	1.14	0.96	0.77	0.72	0.70	0.84	0.88
StdDev	0.35	0.35	0.35	0.32	0.29	0.27	0.26	0.34	0.53	0.51
Skewness	4.42	3.80	3.66	1.27	1.51	4.92	5.20	10.59	24.66	23.28
Kurtosis	47.73	41.08	41.99	6.61	7.42	53.87	62.49	295.65	818.61	776.86

Table A-II. MSCI World Index and MSCI World ESG Index Comparison

The table shows the average returns and standard deviations (in percentages) by cross-sections for the MSCI World Index and the MSCI World ESG Index (computed recursively using the past year of daily data).

		Mar-16	**June-16**	**Sep-16**	**Dec-16**	**Mar-17**	**June-17**	**Sep-17**	**Dec-17**	**Mar-18**	**June-18**
MSCI World	*Mean*	-0.016	-0.022	0.043	0.023	0.076	0.062	0.060	0.082	0.052	0.041
	StdDev	0.889	0.914	0.868	0.789	0.653	0.597	0.435	0.366	0.526	0.563
MSCI World ESG	*Mean*	-0.014	-0.020	0.043	0.030	0.073	0.059	0.054	0.069	0.036	0.036
	StdDev	0.911	0.913	0.841	0.762	0.608	0.554	0.428	0.367	0.517	0.553