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Mitigating Contagion Risk by ESG Investing

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Abstract: We study whether ESG investing may mitigate the risk of contagion among equity mutual funds. More precisely, we measure the impact of fire-sale spillover, propagating throughout the financial system, on funds ranked on ESG aspects. We compare the relative loss of capitalization experienced by high- and low-ranked funds. Contagion, which is indirect since funds are not exposed to counterparty risk, is modeled using a network structure. In cases of deleveraging from funds, fire-sale spillover propagates throughout the network because of common asset holdings among funds. We find that funds' vulnerability to contagion decreases when the level of ESG compliance increases. Moreover, the average relative loss is lower for the high-ranked funds than for the low-ranked ones. The small-size funds mainly drive the result. Our findings indicate that contagion is less effective for high-ranked funds. From a macroeconomic perspective, ESG investing represents a new opportunity for diversification that makes the system more resilient to contagion.

Keywords: ESG investing; contagion risk; market impact; network; indirect contagion

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1. Introduction

The integration of environmental, social, and governance (ESG) factors in the investment decision process is becoming a valuable practice among portfolio managers. Strategies that account for ESG information are usually implemented either by excluding from the investment universe assets in controversial business sectors (negative screening) or by tilting portfolios towards the assets with the highest ESG ranks (best-in-class strategies).

The literature on ESG investing mainly focuses on the relationship between the financial profitability of an investment and its ESG rate. The evidence on the sign of such a relationship is still mixed; it depends on the analyzed period and market and the ESG rating system used. For example, Ref. [1] found that ESG funds significantly underperform conventional funds. Similarly, Ref. [2] showed that a fund's risk-adjusted returns decrease with the level of the fund's ESG score. Ref. [3] introduced a latent variable to measure ESG compliance and found a positive relationship between such a variable and portfolio financial performance. Ref. [4] analyzed the impact of negative screening on the efficient frontier, finding that screening impacts significantly on the opportunity set only when it is based on the environmental criterion. Refs. [5,6] found that, by tilting their portfolios towards assets with higher ESG scores, the investors can earn positive risk-adjusted returns. However, the return advantages are offset by the adoption of negative screening criteria that exclude sin stocks from the opportunity set. Indeed, systematic screening of certain assets leads to a return premium on the screened assets in equilibrium (see e.g., [7–10]).

In turn, a systematic lower demand for the screened assets leads to lower prices and thus to higher expected returns. Consistently with such theoretical prediction, Refs. [11,12] documented that the so-called "sin" stocks deliver higher returns. Such a higher return is justified by the higher riskiness of sin stocks measured for example, via the implied volatility [13].

Most studies have found no statistical difference in the financial performance between high-ESG-ranked funds and conventional funds. Among them we cite [14–16]. It is still unclear if the mixed evidence provided so far is the product of methodological issues [17,18], or is driven by the heterogeneous nature of the ESG dimensions [19].

From a different perspective, we have found evidence in the literature that investing in assets that are high-ranked on ESG reduces the risk of the investment. Firms showing higher levels of compliance with the ESG dimensions mitigate the risk of disputes with the stakeholders [20], lower their exposition to crash risk [21], and reduce the probability of default [22]. Ref. [23] showed that responsible firms with higher product diversification are less exposed to market risk. Ref. [24] found that firms showing high compliance with the social dimension performed better than firms with poor social performance during the 2008–2009 financial crisis. Similarly, Ref. [25] found that, during crisis periods, high-ESG-ranked funds experienced lower downside risk than conventional funds. Even during the recent COVID-19 crisis, ESG investments outperformed conventional ones [26]. In general, ESG investments are perceived as a form of insurance against the higher volatility levels faced by the investors during crisis periods [27]. Consistent with such a finding, Ref. [28] provided empirical evidence that a system of high-ranked ESG funds presents a solid ability to absorb external shocks, mainly if the involved funds have a small market capitalization.

The capability of high-ESG-ranked assets to reduce risk exposures appears to be a well-established feature of ESG investments, even if the literature has not been able so far to unequivocally disentangle the existing relation between ESG rates and asset returns. Hence, the investors may benefit from a general risk reduction by tilting their portfolios towards firms with high ESG scores. This paper aims to analyze the risk associated with ESG investment strategies from a systemic point of view by considering a network of equity mutual funds rated on ESG dimensions. In more detail, following [29], we define a fund vulnerability index measuring the risk of contagion for a fund in case of financial distress propagating throughout the whole network of funds, and we show its relationship with the fund ESG rate. Moreover, we compute the relative market value loss experienced by a fund from fire-sale spillover due to deleveraging from the other funds in the network.

The analysis is performed on a network of more than 5000 funds investing in almost 20,000 assets. We rate funds according to the Globe ESG rates released by Morningstar in 2018. We model contagion risk by considering a bipartite network. Such a network has two sets of nodes: the first one represents funds, while the second set of nodes contains holdings. Any fund is linked to the nodes representing its holdings, and it is only indirectly connected with the other funds in the network through the holdings it has in common with them. Hence, funds in the network are related because of portfolio overlaps in terms of common asset holdings. In such a context, a fund tends to liquidate part of its portfolio when the investors withdraw large amounts of money from the fund [30]. Portfolio deleveraging causes the lowering of prices of the liquidated assets. Hence, if such a fund is highly overlapped with other funds in the network—meaning that a large part of its assets is held in the portfolio by other funds—the overlapping funds may also experience a large loss of value. As a consequence, they may start to liquidate their portfolio as well. Such a mechanism may trigger a cascade of fire-sale spillover that propagates throughout the whole network, hitting assets and funds that were not shocked at the beginning. This is indirect contagion since risk propagation among funds is mediated by the overlap between portfolios also in the absence of a direct link (which would be present in the case of counterparty risk among the nodes).

Indirect contagion among funds has been studied, for example, by [30–32] among the others. To measure the market impact from portfolio deleveraging, we follow [29,33], who modeled the market impact on asset value as a linear function of the assets liquidated [34]. Then, we construct the funds' adjacency matrix associated with the network by computing the liquidity-weighted overlap for any pair of funds in terms of common holdings. In the overlap, any asset weights differently according to its market depth. A more liquid asset, having a higher market depth, has a lower weight in portfolio overlap since its market value loss from deleveraging is lower. On the contrary, a less liquid asset with a lower market depth weighs more in the overlap since it is more responsible for risk propagation.

Given the overlap structure between portfolios, we compute the vulnerability index for any fund as defined in [29], measuring the percentage relative loss of market value experienced by a fund when any other fund in the network liquidates 1% of its assets. We find that the vulnerability index for the funds decreases when the level of ESG compliance increases. In particular, the vulnerability index for the funds with the lowest ESG rates is on average 50% higher with respect to the highest ESG-ranked funds. Moreover, for different fractions of liquidated assets and different levels of ESG compliance, we measure the relative market value that each fund loses when all funds in the network liquidate a fraction of their portfolios. Results show that the average loss is lower for the highest ESG-ranked funds in all cases. In particular, liquidation of 10% of the assets provides a systemic average relative loss of market value which is 98% higher for the lowest ESG-ranked funds than for the highest ESG-ranked funds. The same analysis is also performed by measuring the impact of fire-sale spillover for the large- and the small-size funds within the highest and lowest ESG categories. We find that the small and highest-ranked funds experience a lower loss than the small and lowest-ranked ones. However, for the large funds, the impact of contagion is comparable for the two ESG categories.

Our findings indicate that fire-sale spillover from asset liquidation by funds in the network has a lower impact on the funds with a higher level of ESG compliance. The paper contributes to the literature on ESG investing from a new perspective. Most literature analyzes the risk associated with ESG investing by considering each fund or asset as a stand-alone entity. We instead consider funds as interrelated entities, and the risk of ESG investing is measured in relation to the whole system. In such a framework, highly ranked funds in ESG dimensions seem to be less affected by fire-sale spillover propagating throughout the network. Under this perspective, ESG investing appears to be a new opportunity for diversification for the investors [35] that reduces the exposure to contagion risk. Useful implications are also for policymakers, who may promote the implementation of ESG-based strategies to make the financial system more resilient to systemic events.

The paper is organized as follows. Section 2 sets the hypothesis to test. Section 3 introduces the model, defines the vulnerability index for a fund, and provides a measure of the relative market value loss from portfolio liquidation. Section 4 describes the dataset and presents the results. Section 5 concludes. Section 6 discusses the limitations and possible future extensions of the present analysis.

2. Research Hypothesis

We measure the relative loss experienced by funds in the case of deleveraging from all the funds in the network. We test the alternative hypothesis H_1—the average relative loss for the high-ranked funds $\bar{L}_{High}$ is lower than the average relative loss for the low-ranked funds $\bar{L}_{Low}$—against the null hypothesis H_0–there is no significant difference in the averages—

$$\begin{aligned} H_0: &\quad \bar{L}_{High} = \bar{L}_{Low} \\ H_1: &\quad \bar{L}_{High} < \bar{L}_{Low}. \end{aligned}$$

The same hypothesis is also tested by considering the response of large-size and small-size funds within the high- and low-ESG categories.

Our hypothesis is motivated by three main aspects. First, the higher ESG-ranked funds tend to hold assets with higher ESG scores [36]. Such a set of assets also includes non-mainstream assets. By shifting the opportunity set towards the higher-ESG-ranked assets, funds exploit a different market segment and reduce their overlap with the other funds in the network. Lower portfolio overlap is usually associated with a mitigation of the risk of indirect contagion, leading to a reduction in systemic risk. In line with this argument, we cite [31], who considered a bipartite network of funds and assets and provided a measure of the overlap of funds in the market. Their results indicate that funds investing in less popular assets are less exposed to fire-sale spillover, and therefore such funds experienced lower losses during the 2008 financial crisis. The second aspect is that the demand for high-ESG-ranked assets is usually driven by investors' preference for such stocks. Indeed, responsible investors also consider personal and societal values in their investment decision process [2,37]. Hence, such investors rely on longer-term strategies and are less inclined to liquidate their portfolios in cases of financial distress. As such, high-ESG-ranked funds are less affected by fire-sale spillover from deleveraging. Third, following the general discussion in the Introduction, firms that are highly compliant with ESG factors are less exposed to the stakeholder risk, hence making the investment less risky.

3. The Model

A bipartite network, with two distinct sets of nodes, is the standard framework to study indirect contagion among funds. Funds are modeled as nodes in the first set, while their holdings belong to the second set of nodes. There is no direct link between two funds in such a bipartite network. This feature reflects that two funds are not reciprocally exposed to counterparty risk. Instead, any fund is directly linked only to its constituencies and, as a consequence, two funds are indirectly connected because of common asset holdings.

A fund exposed to large outflows reduces its position to refund investors withdrawing money from the fund [30]. Liquidated assets undergo a drop in value, the extent of which depends on how liquid the assets are. The loss in value of such assets also impacts the value of other funds exposed to those assets. This fact may also force other funds, sharing with the first fund part of their assets, to liquidate their portfolios, thus causing a further drop in values of the common assets and a drop in the value of the other assets in the portfolio. Contagion is indirect since it is not due to direct exposure of one fund to another fund. Instead, it is due to fund exposure to the same assets. Therefore, portfolio overlaps, as measured by common asset holdings, mediate the propagation of fire-sale spillover throughout the network.

Two key ingredients are needed to evaluate the impact of contagion in the network. The first one is the matrix $\mathbf{h}$ of portfolio holdings whose generic element h_{ik} provides the number of shares of asset $k = 1, \ldots, N_A$ held by fund $i = 1, \ldots, N_F$, where N_A and N_F are the number of assets and the number of funds, respectively. By denoting with p_k the price of asset k, the market value MV_i of fund i is then obtained as

$$MV_i = \sum_{k=1}^{N_A} h_{ik} p_k. \tag{1}$$

The second ingredient is a price impact function modeling the effect of liquidation on assets. We use the linear price impact model [34] as in [29,33]. Liquidation of x shares of asset k causes a drop in its value Δp_k given by

$$\frac{\Delta p_k}{p_k} = \frac{x}{\lambda_k}, \tag{2}$$

where λ_k is a measure of liquidity for asset k, which is known as market depth. The more liquid an asset, the higher its market depth, the lower the impact on its price from liquidation. For each asset k, market depth may be estimated from market data as described in [38] or [39], according to the following ratio

$$\lambda_k = c \frac{ADTV_k}{\sigma_k} \tag{3}$$

where c is a constant that is independent from the asset, $ADTV_k$ is the average daily trading volume for asset k, and σ_k is its volatility.

When fund j liquidates a percentage ε_j of its holdings, it causes price pressure on the liquidated assets according to Equation (2). Then, fund i undergoes a loss in market value ΔMV_{ij} because of the assets in common with fund j. Such a loss is expressed as

$$\Delta MV_{ij} = \sum_{k=1}^{N_A} h_{ik} \frac{p_k}{\lambda_k} h_{jk} \varepsilon_j. \tag{4}$$

where we used Equations (1) and (2) with $x = h_{jk}\varepsilon_j$.

The loss in market value in Equation (4) may be expressed in terms of the adjacency matrix Ω associated to the network. Its generic (i, j) element

$$\Omega_{ij} = \sum_{k=1}^{N_A} h_{ik} \frac{p_k}{\lambda_k} h_{jk}, \tag{5}$$

for $i, j = 1, \ldots, N_F$ measures the portfolio liquidity-weighted overlap between funds i and j. Then, Equation (4) reads

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

Note that in the overlap any asset in common has a weight according to the inverse of its liquidity factor. This feature of the model accounts for the fact that a more liquid asset is less affected by liquidation, hence it makes the network more resilient to contagion.

We now compute the relative loss of market value L_i experienced by fund i when any other fund j liquidates a percentage ε_j of its assets

$$L_i = \frac{1}{MV_i} \sum_{j \neq i}^{N_F} \Omega_{ij}\varepsilon_j, \tag{6}$$

where the effect of liquidation by fund i to itself is not accounted for. Following [29], we define the fund vulnerability index VI_i for fund i as

$$VI_i = \frac{1}{MV_i} \sum_{j \neq i}^{N_F} \Omega_{ij}. \tag{7}$$

Such an index is a measure, in terms of relative market value loss, of the vulnerability of a fund to contagion from other funds in the network starting deleveraging. Indeed, the vulnerability index for fund i provides the percentage relative loss in market value experienced by fund i when all the other funds liquidate 1% of their assets. This is obtained by Equation (6) when $\varepsilon_j = 1\%$ for all $j = 1, \ldots N_F$.

4. Empirical Analysis

In this section we first describe the dataset and the empirically obtained network. Then, we compute the vulnerability to contagion for each fund in the network, and we compare the average relative loss of market value due to portfolio liquidation experienced by the highest-ranked funds with that for the lowest-ranked funds.

4.1. Dataset Description

We consider a cross-section of equity mutual funds, investing either globally or in a specific country region, rated on ESG factors by Morningstar in 2018. The initial sample consists of 9849 open-end equity mutual funds investing in 28,561 assets. The dataset is built by matching information from different databases. Morningstar Direct (MD) provides ESG rates for different fund share classes. Fund share classes are aggregated to a single fund using the fund identifier ($FundId$) in MD [40]. Portfolio holdings are obtained from Morningstar European Data Warehouse (EDW) for each fund. Financial data as trading volumes or returns for the assets are taken from Refinitiv (DATASTREAM).

Standard cleaning criteria are applied to the sample before carrying out the analysis. We keep in the sample only funds whose total capitalization is provided and for which holding weights account for at least 80% of portfolio capitalization. Moreover, funds whose holding-weight sum is greater than one are eliminated. To ensure a minimum level of fund diversification, we eliminate from the sample those funds that are too small in terms of capitalization (cut-off at the 2.5-th percentile) or of the number of assets in the portfolio (cut-off at the 2.5-th percentile). The screened sample consists of funds having at least a capitalization of 100,000 USD and investing in at least 14 assets. The filter on very small funds does not impact the results since such funds account for less than 0.05% of the total capitalization. Moreover, they are poorly overlapped with the other funds in the network. Hence, they are irrelevant from a systemic point of view. Screening criteria are also used at the asset level. We keep in the sample only assets with daily observations of the returns and trading volumes over one past year (by taking as a reference date the middle of the year, we consider the time-span end of June 2017–end of June 2018). This leads to an estimation sample of $N_F = 5625$ funds investing in N_A = 19,985 assets. Portfolio holdings are then normalized to one for each fund in the sample.

The Morningstar Sustainability Rating System rates funds according to five classes: High (H), Above Average (AA), Average (A), Below Average (BA), and Low (L). Morningstar ratings are based on company ESG scores. To receive a portfolio ESG score, at least 67% of the assets under management in the fund must have a company ESG score. $H(L)$ funds are those in the top (bottom) 10% of the score distribution. BA funds have a score that is between the 10-th percentile and the 32.5-th percentile of the score distribution. A funds are those in the next 35% of the distribution. AA funds are ranked in the range between the 67.5-th percentile and the 90-th percentile. (For further details see the Morningstar Sustainability Rating at https://www.morningstar.com/content/dam/marketing/shared/research/methodology/744156_Morningstar_Sustainability_Rating_for_Funds_Methodology.pdf, accessed on 31 January 2022). Out of $N_F = 5625$ mutual funds in our sample, 530 are ranked as L, 1312 as BA, 2020 as A, 1272 as AA, and 491 funds are ranked as H.

Funds belonging to different ESG categories invest in different sets of assets that intersect with each other. Table 1 reports the dimension of the investment sets for the different ESG categories as well as the number of assets in common. For example, Table 1 shows that the High-ranked funds invest globally in 7308 assets. Low-ranked funds invest in 15,027 assets. Out of 15,027 assets, 6885 are in common with the investment set of the High-ESG-ranked funds. By looking at the last column, we see that the High-ESG-ranked funds are those with the lowest number of assets in common with the funds in the other categories. This is, of course, due to the fact that by tilting their portfolios towards the assets with the higher ESG performance, the High-ESG-ranked funds shift their opportunity set towards a segment of the market that the other funds do not exploit. This feature lowers the overlap of such funds with the other funds in the network.

Table 1. Dimension of the investment sets across ESG categories. The table shows the number of assets held by all the funds belonging to different ESG categories on the first diagonal. The number of assets in common between different ESG classes is also shown.

	L	BA	A	AA	H
L	15,027	13,662	14,011	10,799	6885
BA		16,014	14,475	10,878	7086
A			17,583	11,187	7072
AA				11,711	7072
H					7308

Table 2 provides the main statistical indicators of fund distributions for the relevant variables across ESG categories, as taken at the end of June 2018. Table 2 (Panel A) shows descriptive statistics for the number of assets held by each fund. Table 2 (Panel B) reports descriptive statistics for the funds' Herfindahl–Hirschman index built from portfolio weights. Table 2 (Panel C) provides statistical indicators for the funds' capitalization (in millions of USD) as measured by the total net assets (TNA). Table 2 (Panel D) shows funds' annualized average daily returns computed over the past year (end of June 2017–end of June 2018).

Table 2. Descriptive statistics at fund-level across the ESG categories. The table reports funds' descriptive statistics across ESG categories: the number of assets (Panel A), the Herfindahl–Hirschman index (Panel B), the total net assets in millions of USD (Panel C), and the annualized average daily returns in percentage (Panel D). The five ESG categories are High (H), Above Average (AA), Average (A), Below Average (BA), and Low (L).

	Number of Assets—Panel A				
	L	BA	A	AA	H
Min	14	16	16	15	15
Max	7807	7426	9699	4440	2661
Mean	152	183	186	117	83
StdDev	607	512	409	220	189
Skewness	8.35	7.06	9.35	8.92	10.81
Kurtosis	81.53	67.11	165.94	135.36	136.28
	Herfindahl–Hirschman Index—Panel B				
	L	BA	A	AA	H
Min	0.00	0.00	0.00	0.00	0.00
Max	0.22	0.17	0.27	0.19	0.21
Mean	0.03	0.03	0.03	0.03	0.03
StdDev	0.02	0.02	0.02	0.02	0.02
Skewness	3.01	1.98	2.46	1.89	3.37
Kurtosis	23.49	11.66	17.20	10.14	22.50
	Total Net Assets (Millions of USD)—Panel C				
	L	BA	A	AA	H
Min	0.13	0.10	0.10	0.10	0.10
Max	3159.51	3129.50	3135.28	3055.27	3128.60
Mean	177.84	166.92	184.46	196.11	204.68
StdDev	380.54	370.59	418.06	406.29	435.75
Skewness	3.95	4.13	4.04	3.71	3.47
Kurtosis	22.21	23.19	21.51	18.97	16.67
	Annualized Average Daily Returns (%)—Panel D				
	L	BA	A	AA	H
Min	−32.21	−114.34	−73.12	−35.15	−28.52
Max	39.70	48.53	324.70	35.17	29.22
Mean	6.38	4.99	4.84	4.54	3.72
StdDev	10.45	8.62	13.13	7.47	6.99
Skewness	−0.02	−2.03	12.99	−0.27	−0.28
Kurtosis	4.38	33.18	291.58	4.84	5.17

Table 3 reports the cross-sectional average and standard deviation of the daily standard deviation of asset returns over the past year (Panel A) and of the average daily trading volume of assets as measured by the number of traded shares (Panel B). Daily standard deviations for asset returns and average daily trading volumes are computed considering the period end of June 2017–end of June 2018. Figures for volumes are in millions of traded shares. For any ESG category, the assets used to compute descriptive statistics are those in which funds in that category invest. The standard deviation of the returns and the average trading volume are the only variables we need to compute the market depth for each asset as defined in Equation (3). Table 3 shows that the assets in the investment universe of the High-ranked funds are less risky than the assets in other categories (Panel A). Moreover, they have the highest average trading volume (Panel B).

Table 3. Descriptive Statistics at asset-level across the ESG categories. The table shows asset descriptive statistics across ESG categories for the standard deviation of daily returns over the past year (Panel A) and the average daily trading volume as measured by the number of shares traded (Panel B). Assets in a particular ESG category are those in which funds invest.

	Standard Deviation (%) of Daily Returns—Panel A				
	L	*BA*	*A*	*AA*	*H*
Mean	2.22	2.15	2.17	2.01	1.93
StdDev	1.17	1.10	1.09	0.95	0.89
	Average Daily Trading Volume (in Millions of Shares Traded)—Panel B				
	L	*BA*	*A*	*AA*	*H*
Mean	3.83	4.40	4.72	4.75	5.67
StdDev	160.40	155.61	148.53	181.79	228.80

4.2. Results

To implement the model in Section 3, first, we need to calibrate the price impact model in Equation (3), i.e., we have to fix the constant c. We estimate c by imposing that the average relative loss in market value experienced by all funds in the network is 1% when all funds liquidate 1% of their assets. Another proposal is given in [41,42], where the authors estimate c by imposing that the median loss value for the assets in the sample is 440 bsp for 10 billion of USD liquidated. Our choice is in the same spirit as them, having the advantage of improving the readability of results (in a linear model, results depend linearly on c. Hence, to avoid the arbitrariness of calibration, findings have to be given in relative terms; for example, comparing results for an ESG category with those of another ESG category).

Portfolio overlaps mediate contagion risk from fire-sale spillover between funds in the network. The overlap of the High-ranked funds with all the funds in the network—as measured by the elements of the adjacency matrix in Equation (5)—is lower than the overlap of the Low-ESG-ranked funds with all the funds in the network. This is shown in Figure 1, where the highest thirty elements of the sub-adjacency matrix for the High-ranked funds are compared with the highest thirty elements of the sub-adjacency matrix for the Low-ranked funds. The reduced overlap for the High-ESG-ranked funds follows from the fact that such funds share the lowest number of assets with the funds in the other categories, as shown in Table 1. The asset's market depth then amplifies this effect as in Equation (5). Lower overlaps, in turn, mitigate the risk of propagation of a local shock to the entire financial network.

Then, we compute the vulnerability index for each fund in the network as in Equation (7). Figure 2 shows the cross-section average (upper panel) and standard deviation (lower panel) of the vulnerability index of the funds across the different ESG categories. Results are standardized so that the average vulnerability index of the High-ranked funds is equal to 1.

Figure 2 shows that fund vulnerability decreases with ESG compliance. In particular, the vulnerability is higher for the Low-ranked funds and lower for the High-ranked ones. In detail, the vulnerability index for the Low-ESG-ranked funds is on average 50% higher than the vulnerability of the High-ESG-ranked funds. In other terms, for 1% of liquidated assets, the average relative loss of market value for the Low-ranked funds is 50% higher than the same quantity for the High-ranked funds with a standard deviation that is almost double that for the High-ranked funds. Such a result can justify why, during crisis periods, ESG funds were able to mitigate their losses [24–26].

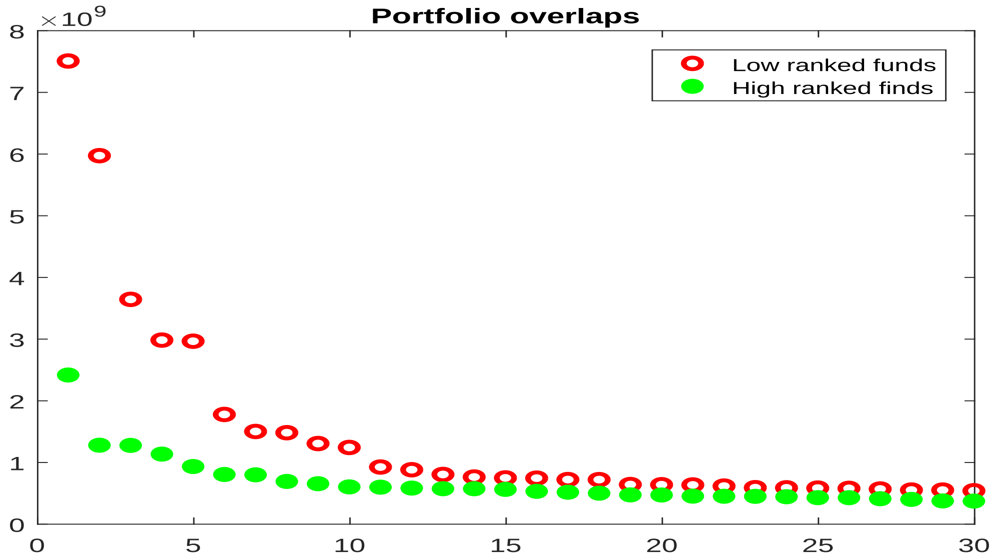

Figure 1. Portfolio overlaps. The figure compares the highest thirty portfolio overlaps, computed according to Equation (5), of the High-ranked funds (full circles) and of the Low-ranked funds (empty circles) with all the funds in the network.

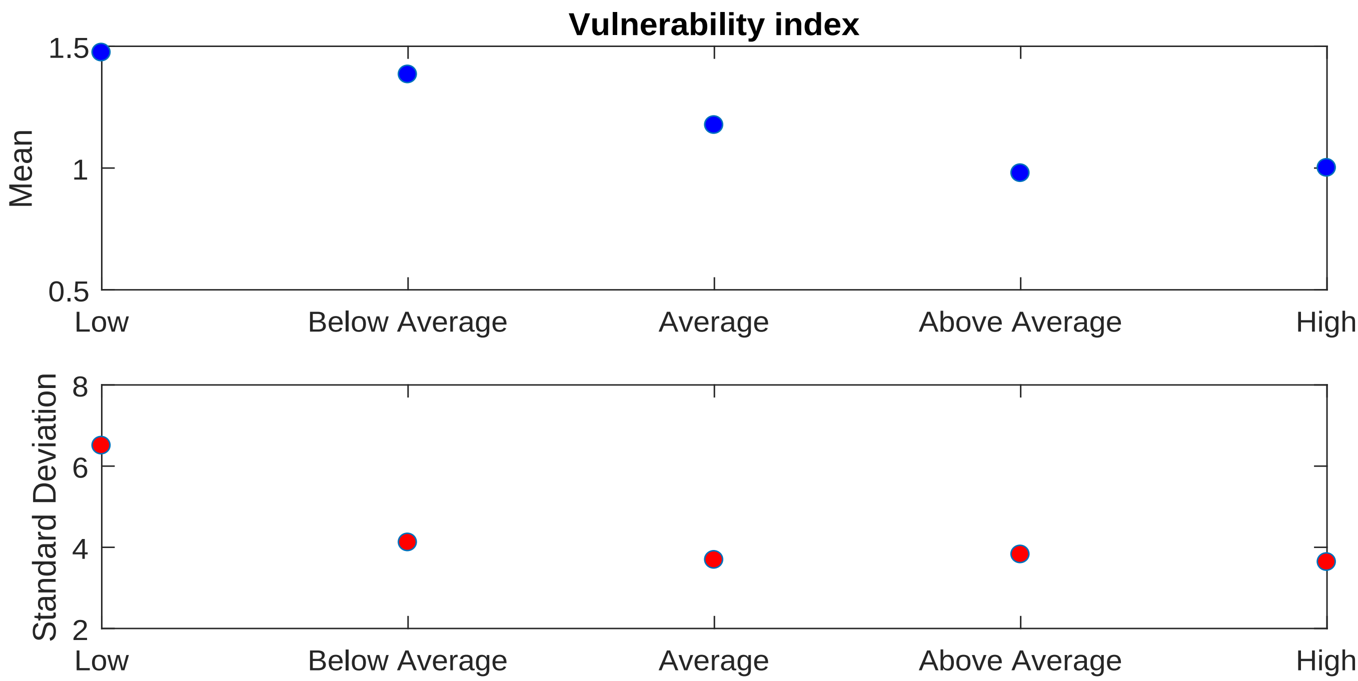

Figure 2. Fund vulnerability index. The figure shows the cross-section average (**upper panel**) and standard deviation (**lower panel**) of the vulnerability index as given in Equation (7) of the funds across different ESG categories.

Figure 3 shows the average of the relative market value loss (6) experienced by the High- (crossed line) and Low (dotted line)-ranked funds, when different fractions of assets are liquidated by all the funds in the network. We only report results for these two categories since they represent the extreme cases of our dataset, and the difference in the level of ESG compliance is the highest for them. The left panel shows results when liquidation is implemented in one step, while the right panel reports the case when the same quantity of assets is liquidated in ten steps. Results indicate that the average relative loss of market value is always lower for the High-ESG-ranked funds for any given fraction of liquidated assets. For example, when funds liquidate 10% of their assets in one step, Figure 3 shows that the Low-ESG-ranked funds lose 98% more than the High-ESG-ranked funds. Slower liquidation (right panel) has, of course, a weaker impact on the market value loss for both the Low- and the High-ESG-ranked funds. In conclusion, Figure 3 shows that contagion is less effective for the High-ESG-ranked funds.

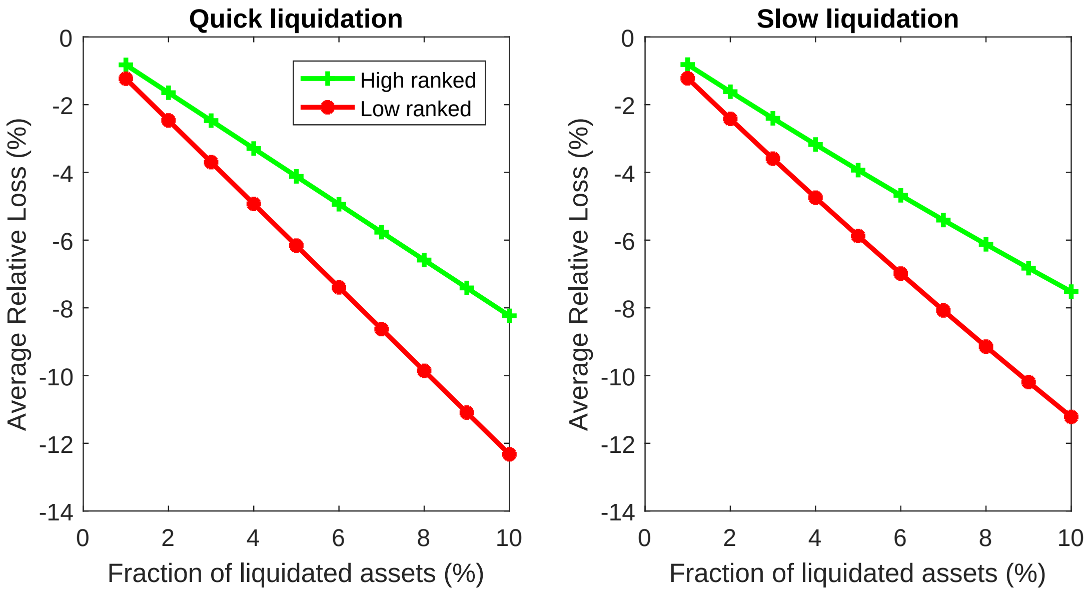

Figure 3. Average of the relative market value loss. The figure shows the average of the relative market value loss (6), achieved by the High-ranked funds (crossed line) and by the Low-ranked funds (dotted line) for different fractions of assets liquidated by all the funds in the network. Liquidation is implemented either in one step (**left panel**) or in ten steps (**right panel**).

Table 4 reports the difference $High - Low$ in the average relative loss of market value for different fractions of assets liquidated by all the funds in the network when liquidation is implemented either in one step (column 2-3-4) or in 10 steps (column 5). A two-sample t-test shows that, on average, the relative market value loss experienced by the High-ranked funds is significantly lower than that for the Low-ranked ones with a p-value equal to 0.063 for the quick liquidation case (column 2) and 0.064 for the slow liquidation case (column 5). The same test is performed when the comparison is made for the Large, Small, respectively, funds (top 33%, bottom 33% respectively, of the total net assets distribution within the High- and Low-ESG categories). Table 4 shows that the average difference is not significant for the large-size funds. However, the average difference is significant for the small funds, with a p-value equal to 0.061. Hence the better systemic performance of the High-ranked funds in terms of a higher resilience to contagion is driven by the small-size funds that, by construction, are those presenting the lowest overlaps with the other funds in the network.

Table 4. Difference $High - Low$ of the average relative loss in market value. The table shows the difference (High minus Low) of the average relative loss in market value for different fractions of assets liquidated by all the funds in the network when liquidation is implemented either in one step or in ten steps. Results are also shown for the large-size (top 33%) and small-size (bottom 33%) categories.

	Quick Liquidation			Slow Liquidation
$\varepsilon(\%)$	$(H-L)(\%)$	LARGE $(H-L)(\%)$	SMALL $(H-L)(\%)$	$(H-L)(\%)$
1	0.41 (*)	0.02	0.73 (*)	0.40 (*)
2	0.82 (*)	0.04	1.47 (*)	0.80 (*)
3	1.23 (*)	0.05	2.20 (*)	1.19 (*)
4	1.64 (*)	0.07	2.94 (*)	1.57 (*)
5	2.05 (*)	0.09	3.67 (*)	1.94 (*)
6	2.45 (*)	0.11	4.41 (*)	2.31 (*)
7	2.86 (*)	0.13	5.14 (*)	2.67 (*)
8	3.27 (*)	0.15	5.88 (*)	3.02 (*)
9	3.68 (*)	0.16	6.61 (*)	3.36 (*)
10	4.09 (*)	0.18	7.35 (*)	3.70 (*)

The table also reports whether a two sample *t*-test is significant at 10% (*).

5. Conclusions

ESG investing is at the center of a great interest among investors and policymakers. The former are attracted by such investments either for ethical reasons or because they see them as an opportunity for financial profitability. The latter recognize in ESG investments the financial driver towards sustainable development. Moreover, ESG investments reduce exposure to different sources of risk, a desirable feature, especially in periods when markets are turbulent.

We have contributed to the debate on the opportunities associated with ESG investments by studying the risk in ESG investments from a systemic perspective. We carried out our analysis by considering a network of equity mutual funds rated on ESG aspects, where funds are not stand-alone entities but are interconnected since they are exposed to the same assets, although with different percentages.

High-ESG-ranked funds are good candidates to make the financial system more resilient to contagion. Indeed, such funds, by tilting their portfolios towards the highest-ESG-ranked assets, also invest in non-mainstream assets. Therefore, shifting the investment universe towards a new market segment makes the high-ESG-ranked funds less overlapped with the other funds in the network, and hence less exposed to contagion in cases of financial distress. Moreover, responsible investors tend to consider longer horizons for their strategies. High-ranked funds are then less affected by fire-sale spillover.

Specifically, we examined a network of funds characterized by different levels of ESG compliance. First, we measured the vulnerability of each fund to contagion from other funds starting deleveraging of their positions. We found that the average vulnerability decreases with the level of ESG compliance. Second, for different levels of asset liquidation, we measured the impact, in terms of funds capitalization, of fire-sales spillover. Results confirm that the loss is lower for the High-ranked funds and that such a result is mainly due to the Small-size funds.

Our results indicate that contagion is less effective among funds with higher ESG rates and provide a first indication that ESG investments could make the financial system more resilient to contagion while increasing its stability, even though such results were obtained on a particular dataset and further analysis has to be conducted to confirm them.

6. Limitations and Outlook

In this section, we highlight some critical aspects of our study. Each of them will require further extensive analysis beyond the scope of this work.

The first aspect is related to the dataset. Our findings rely on the Morningstar Sustainability rating system, which is the most comprehensive and reliable dataset on funds. However, it is a well-known fact that different sustainability rating systems may evaluate the ESG performance of firms differently and may then assign completely different ratings to the same asset. Such an inconsistency is then inherited by funds, since funds' ESG rates are based on their holdings rates. Hence, any analysis on ESG investing is intrinsically endowed with an ESG measurement bias. The whole analysis should be implemented on other rating systems to evaluate the impact of such an issue on the results.

The second aspect concerns the time span analyzed. We considered a cross-section of funds at a particular date, and we estimated the financial variables we needed for the analysis for a time span of one year. However, funds may react differently to deleveraging in turbulent or quiet periods. Hence, further analysis should be performed to test different time spans to confirm the results.

Finally, the third aspect is related to the model. We implemented a linear market impact model. Such a model is widely used in the literature since it is simple to interpret. Moreover, for small liquidated volumes, it provides a good approximation of reality. However, it may overestimate the losses for larger volumes, and a different model could be more appropriate.

Despite such limitations, the results are encouraging and, if confirmed, indicate that investment strategies based on ESG factors may be the instrument for policymakers and investors to make the system less vulnerable to a systemic financial shock.

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