CEIS TOR VERGATA Research Papers

Università di Roma Tor Vergata

ISSN 2610-931X

CEIS Tor Vergata

RESEARCH PAPER SERIES

Vol. 18, Issue 7, No. 498 – July 2020

ESG Investing: A Chance To Reduce Systemic Risk

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July 3, 2020

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 rates. Fire sales spillover from portfolio liquidation propagates from one fund to another because of indirect contagion mediated by common asset holdings. We find that the vulnerability of funds to contagion decreases with the level of ESG compliance. Contagion is less effective for higher ranked funds than for lower ranked ones. In particular, for different levels of portfolio liquidation, the relative market value loss of the highest ESG ranked funds is lower than the loss experienced by the lowest ESG ranked counterpart.

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

Acknowledgments: The authors are grateful to all the participants to the 2019 Villa Mondragone Conference, to the 2019 University of Perugia Workshop on Socially Responsible Investments, to the 2019 Italian SRI week and to the XXI Workshop on Quantitative Finance. This research is partially funded by Morningstar (contract. n. OPP635470), Etica Sgr (ref.n. R01-2019) and Fondazione Cassa di Risparmio di Perugia (ref.n. 2017.0226.021). This is part of the project "Socially Responsible Investments: only a transient fad or a real change of the investment paradigms?" founded by University of Perugia – *Fondo Ricerca di Base 2018*.

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1 Introduction

Systemic events, such as the Lehman Brothers default in September 2008, may generate financial distress that then wide-spreads across systems. 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 collapse at the same time; and (3) a negative externality generated in one financial institution propagates to the others. In the last scenario, we denote the risk of a particularly violent transmission, that may lead to market crashes, as contagion risk (De Bandt and Hartmann, 2015).[1]

Contagion can be direct, due to counterparty risk, or indirect, because of exposure to common assets. Indirect contagion is the main channel of risk propagation when financial institutions are not exposed to counterparty risk to each other. 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. Such a liquidation creates price pressure in the liquidated securities. Then also the other financial institutions investing in the same securities may experience a loss of value in their portfolios. Such a 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 entire financial system.

Indirect contagion in the interbank system is studied by Cont and Schaanning (2019), among the others, who analyze the impact of portfolio deleveraging. However, risk may propagate in the interbank system also through other channels: Fink et al. (2016) model transmission of risk from one bank to another via asset devaluation and credit quality deterioration; Kanno (2015) studies direct contagion for global banking system by using a network centrality measure; Corsi et al. (2018) propose a flight-to-quality indicator to identify periods of turbolence in the market.

Indirect contagion is the main channel of risk propagation among mutual funds whose portfolios have in common part of the assets. Coval and Stafford (2007) analyze the cost of asset fire sales in equity market caused by mutual funds transactions. Flori et al. (2019) 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

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

that funds investing in less popular assets generally outperform those investing in more popular financial instruments. Braverman and Minca (2018) measure the overlap between mutual funds by weighting different holdings in portfolio by a liquidity factor and propose different measures of vulnerability that are highly 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.

Environmental, Social, and Governance (ESG) investing represents still an unexplored field of research when dealing with a network 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 such a question by considering the cross section of open-end equity mutual funds that are ranked for ESG by Morningstar in June 2018. ESG rates and information at fund level (Morningstar Direct) are matched with information at holdings level (Morningstar European Data Warehouse) and at assets level (Refinitiv) to built a bipartite network of interconnected funds with different levels of ESG compliance. A bipartite network has two sets of nodes. In our context, the first set is for funds, the second one is for holdings. Any node representing a fund is connected with the nodes representing its holdings, and only indirectly with another fund, through the holdings they have in common. Indirect contagion is then mediated by the overlap between portfolios and it is due to fire-sales spillover from liquidation.

To model indirect contagion we follow Braverman and Minca (2018) and Cont and Schaanning (2019). In particular, we model market impact on asset value as a linear function of the assets liquidated (Kyle, 1985). Then, we construct the funds adjacency matrix by computing the overlap for any couple of funds in the network in terms of common holdings. 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 of indirect contagion between funds. Differently, an asset with a low market depth has a large weight in the overlap.

Given the overlap structure between portfolios, we compute the vulnerability index VI for any fund as defined in Braverman and Minca (2018), 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 with the level of ESG compliance. In particular the vulnerability index for the funds with the lowest ESG ranking is on average 50% higher with respect to the highest ESG ranked funds. Second, for different fractions of liquidated assets, and different levels of ESG compliance, we measure the relative market value which is lost by all the funds with that level of ESG compliance, when all funds in the network liquidate a fraction of their portfolios. Since our model is linear, such a quantity is also proportional to the average relative market value loss experienced by funds due to liquidation by a fund at a time. Results show that the loss is lower for the highest ESG ranked funds in all the cases. In particular, liquidation of 10% of the assets provides a systemic loss of market value which is 60% higher for the lowest ESG ranked funds than for the highest ESG ranked funds.

Our findings indicate that fire-sales spillover from asset liquidation by funds in the network has a lower impact on the funds with a higher level of ESG compliance. Results are driven by the fact that higher ESG ranked funds are less overlapped with the other funds in the network and a lower portfolio overlap is usual associated to a mitigation of the risk of indirect contagion leading consequently to a reduction in systemic risk.

The lower overlap is due to two different aspects. Higher ESG ranked funds tend to hold assets with higher ESG scores (Joliet and Titova, 2018). Such a set of assets has in common some assets with the investment set of the other funds. But it includes also not mainstream assets that are not considered by the other funds. By shifting the opportunity set towards the higher ESG ranked assets, funds explore a different niche of the market. This fact reduces the overlap. The reduction in portfolio overlap is reinforced by the market depth of the single assets in portfolios that is higher for the higher ESG ranked assets. Indeed, the demand for ESG assets is driven by investors preference for such stocks. Those investors are reluctant to sell these assets even during crisis periods. Such a result can be justified by the existence of a multi-attribute utility function for responsible investors that incorporate a set of personal and societal values in their investment decisions (El Ghoul and Karoui, 2017 and Bollen, 2007). These features make the return of higher ranked assets less volatile (Becchetti et al., 2015).

The paper is organized as follows. Section 2 is a short review of literature on ESG investing. Section 3 introduces the model, constructs the network and provides a measure of the market value loss from portfolio liquidation. Section 4 describes the dataset and compares the vulnerability index and the market value loss for funds with different ESG rates. Section 5 concludes.

2 Literary review on ESG Investing

Demand for ESG investing surged in the recent years. The US Social Investment Foundation (2016, 2018) reports that the total value of assets under management in the United States subject to ESG screening amounted to $11.06 trillion in 2018 – an increase of 44% relative to 2016. At global level it reached $30.07 trillion, an increase of 34% since 2016 (Global Sustainable Investment Alliance, 2016, 2018). The increasing demand for ESG assets could be motivated by: (1) favorable risk/return characteristics of ESG assets (Becchetti et al., 2018), or (2) the investor preference for such assets unrelated to risk/return considerations (Fama and French, 2007).

Systematic screening of certain assets leads to a return premium on the screened assets in equilibrium (see e.g. Pastor et al., 2019, Pedersen et al., 2019, Heinkel et al., 2001 and Merton, 1987). Intuitively, a systematic lower demand for the screened assets leads to a systematic lower price and thus to higher expected returns. Consistently with such theoretical prediction, Hong and Kacperczyk (2009) and Luo and Balvers (2017) document that the so-called "sin" stocks deliver higher returns. The vast majority of the literature find mixed evidences about the existing relation between risk-adjusted returns and ESG investing. Herzel et al. (2012) analyze 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. Bauer et al. (2007) 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. On the contrary, Kempf and Osthoff (2007) and Glushkov and Statman (2009) find that by tilting their portfolios towards assets with higher ESG scores, the investors can earn positive risk-adjusted returns. Yet, the return advantages are offset by the adoption of negative screening criteria that exclude sin stocks from the opportunity set. Nicolosi et al. (2014) introduce a latent variable to measure the ESG compliance and find a positive relationship between such a variable and portfolios financial performance.

However, most of the studies find no statistical difference in the 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 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 the result is not statistically significant for most of the countries analyzed when looking at risk-adjusted returns.

It is still unclear if the mixed evidences provided so far are the product of methodological issues (Ciciretti et al., 2019 and Chordia et al., 2017), or are driven by the heterogeneous nature of the ESG dimensions (Galema et al., 2008).

By a different perspective, also the existing relation between ESG investing and risk has been object of investigation. Kim et al. (2014) find that firms with a higher standard of transparency engage in less harmful news hoarding, hence lowering their exposition 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 defaults. Such a finding supports the mitigating effect of ESG on crash risk. In this line, Becchetti et al. (2018) show that firms registering lower ESG scores are more exposed to the risk of facing future litigation with the stakeholders, namely the stakeholder risk. Becchetti et al. (2015) show that ESG investing reduces idiosyncratic risk exposure. Similar considerations apply to the systematic risk component too. In this respect, Albuquerque et al. (2018) show that responsible firms have higher profitability and lower market risk exposure. Such characteristics are more pronounced among firms with higher product diversification. Lins et al. (2017) show that, firms with a 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. Such a result suggests that investing in social capital strengths the relationship between stakeholders and investors, and a more substantial relation pays off when the overall level of trust in corporations and markets is affected by a negative shock. Similarly, Nofsinger and Varma (2014) find that ESG funds outperform conventional funds during crisis periods, but the dampening of downside risk comes at the cost of lower returns during non-crisis periods. As such, ESG investing can be seen as a shield during periods of market turmoil.

In summary, even if the literature has not been able so far to unequivocally disentangle the existing relation between ESG investing and returns, the capability of these assets to reduce risk exposures appears to be one of their peculiar characteristics. Hence, by tilting their portfolios towards firms with high ESG scores, the investors may benefit from a general risk reduction.

3 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 while nodes in the second set are their constituencies. A node in the funds set is linked only to the nodes in the assets set representing its holdings. Two funds are indirectly connected through their common holdings.

In this framework, a local shock may propagate throughout the whole bipartite network. Contagion in a network of funds is indirectly mediated by common asset holdings. 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 on the value of funds which are not initially hit by it but having assets in common with the shocked fund. If a second fund experiences a large loss as a consequence of liquidation by the shocked fund, it is possible that also the second fund has to liquidate part of its assets. In doing so, it causes a further drop in the value of the assets in common with the first fund and a drop in the assets value of the other holdings. Hence, the initial shock may trigger fire sales spillover which propagates throughout the entire network of funds.

In what follows we formalize the mechanism of propagation of a shock in the network. Let us consider a bipartite network with N_F funds investing in N_A assets. Following Cont and Schaanning (2019) and Braverman and Minca (2018) we assume a linear price impact model (Kyle, 1985). Liquidation of x shares of asset k impacts on its price P_k according to

$$\frac{\Delta P_k}{P_k} = \frac{x}{\lambda_k}, \tag{1}$$

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

$$\lambda_k = c\frac{ADTV_k}{\sigma_k} \tag{2}$$

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.

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

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

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

$$\Delta MV_i = \sum_{k=1}^{N_A} \alpha_{ik} \Delta P_k. \tag{3}$$

By using Equation (1) with $x = \alpha_{kj}\varepsilon_j$ and Equation (3), we obtain the loss of market value ΔMV_{ij} experienced by fund i when fund j liquidates a fraction ε_j of its holdings

$$\Delta MV_{ij} = \sum_{k=1}^{N_A} \alpha_{ik} \frac{P_k}{\lambda_k} \alpha_{kj} \varepsilon_j. \tag{4}$$

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

$$\Omega_{ij} = \sum_{k=1}^{N_A} \alpha_{ik} \frac{P_k}{\lambda_k} \alpha_{kj}. \tag{5}$$

The term Ω_{ij} measures the overlap between portfolios for fund i and j respectively and can be used to rewrite the market value loss given in Equation (4) 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

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

where the effect of liquidation by fund i to itself is not accounted for.

Following Braverman and Minca (2018), a vulnerability index VI_i for any fund i is defined as

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

The vulnerability index for fund i is a measure of the percentage relative loss of 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 $j = 1, \ldots N_F$.

More in general, the total relative loss of market value experienced by all the funds when any fund j liquidates a fraction ε_j of its assets is

$$Loss = \frac{1}{MV}\sum_{i,j=1}^{N_F}\Omega_{ij}\varepsilon_j, \tag{8}$$

where $MV = \sum_{i=1}^{N_F} MV_i$ is the total market value of all the funds; the loss of value caused by a fund to itself is also accounted for in Formula (8). By denoting with I_c a set of indexes labeling funds in a particular ESG category c, from Equation Equation (8) we can obtain also the relative market value loss $Loss_c$ which is lost by all the funds in that ESG category due to liquidation from any fund in the network

$$Loss_c = \frac{1}{MV_c}\sum_{i\in I_c}\sum_{j=1}^{N_F}\Omega_{ij}\varepsilon_j, \tag{9}$$

where $MV_c = \sum_{i\in I_c} MV_i$ is the total market value of all the funds in the ESG category c. [2]

Notice that Equation (8) can be rewritten as

$$Loss = N_F \frac{1}{N_F}\sum_{j=1}^{N_F}\left(\frac{1}{MV}\sum_{i=1}^{N_F}\Omega_{ij}\varepsilon_j\right), \tag{10}$$

where the terms in parenthesis is the total relative loss experienced by all the funds when fund j liquidates a fraction ε_j of its assets. Hence, Equation (10) shows that the total relative loss obtained when all funds liquidate their portfolios at the same time is proportional to the average relative loss experienced by all funds due to liquidation by a fund at a time. Such a feature is possible only because we are dealing with a linear model.

We highlight that Equations (6–10) measure losses at first order, and do not account for feedback effects. Indeed, liquidation by a given fund i impacts on 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

[2] See Section 4.1 for the ESG categories we use.

the market value loss caused by fund i, its action may cause a further drop in the market value of fund i.

4 Empirical analysis

We construct a bipartite network containing equity mutual funds characterized by different levels of compliance with ESG aspects. First, we describe the dataset. Then, we compute the vulnerability to contagion for any fund in the network and we compare the 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 cross-sectional data of June 2018 retrieved from Morningstar Direct (MD) dataset, that reports data at the fund share class level. Mutual-fund-share-class-level observations are first aggregated to one fund-level observation using the unique fund identifier ($FundId$) in MD (Patel and Sarkissian, 2017). Then funds are matched with Morningstar Sustainability Rating System dataset to retrieve the ESG score for any fund in the dataset (see below for a description). The resulting sample consists in 9849 open-end equity mutual funds rated on ESG aspects investing, globally or in specific macro-geographic/country, in 28561 assets. For these funds we are able to additionally retrieve the cross-sectional data at portfolio holdings-level from Morningstar European Data Warehouse (EDW).

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 at least for the 80% of portfolio capitalization. Funds whose holdings sum to a number higher than 100% are also eliminated. Finally, we eliminate from the sample those funds that are too small in terms of TNA or of number of assets in portfolio thus ensuring a minimum level of internal diversification for the funds in the dataset. [3] Asset prices and trading volumes at

[3]The funds eliminated are those whose TNA is lower than the 2.5-th percentile of the cross sectional TNA distribution or investing in less than the 2.5-th percentile of the cross section number of assets distribution. Then the remaining funds have at least a capitalization of 100000 USD and invest at least in 14 assets. Results are robust for different cutoffs of the distributions.

Table I. Dimension of the investment sets across ESG categories

The table shows the number of assets globally held by funds belonging to different ESG categories. The number of assets in common between different ESG classes is also shown.

	L	*BA*	*A*	*AA*	*H*
L	15027	13662	14011	10799	6885
BA		16014	14475	10878	7086
A			17583	11187	7072
AA				11711	7072
H					7308

firm-level are taken from Refinitiv (DATASTREAM). We keep only assets whose historical series of daily returns and daily trading volumes are available over the last past year. This leads to an estimation sample of $N_F = 5625$ funds investing globally in $N_A = 19985$ assets. Portfolio holdings are then normalized to 1 for each fund in the sample.

Morningstar Sustainability Rating System rates funds according to five classes: High (H), Above Average (AA), Average (A), Below Average (BA), 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. [4] $H(L)$ funds are those in the top(bottom) 10% of the score distribution. BA funds have a score which 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. [5] 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 to each other. Table I reports the dimension of the investment sets for the different ESG categories as well as the number of assets in common. For example Table I shows that the High ranked funds invest globally in 7308 assets. Low ranked funds invest in 15027 asset. Out of 15027 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 rated funds shift their opportunity set toward a segment of the market that is not exploited by the other funds.

[4]The threshold of 67% is also used in El Ghoul and Karoui (2017) who construct their own ESG fund score.
[5]For further details see the Morningstar Sustainability Rating at Morningstar Sustainability Rating.

Table II. 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 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), 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
$Kurtorsis$	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
$Kurtorsis$	23.49	11.66	17.20	10.14	22.50
	Total Net Assets (millions 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
$Kurtorsis$	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
$Kurtorsis$	4.38	33.18	291.58	4.84	5.17

Table II provides the main statistical indicators for the funds distributions of the relevant variables across ESG categories. Table II (Panel A) shows some statistics for the number of assets held by each fund. Table II (Panel B) reports the descriptive statistics for the funds' Herfindahl-Hirschman index built from portfolio weights. Table II (Panel C) provides statistical indicators of the funds capitalization (in millions USD). Table II (Panel D) shows funds annualized average daily returns.

High ESG ranked funds invest in the lowest number of assets (Panel A). However, they hold on average 83 assets in portfolio, which is enough for a portfolio to be well diversified. The kurtosis is very high for all the categories and skewness is always positive. Then, the distributions have fat right tails. A relevant information content for portfolio diversification is given by the Herfindahl-Hirschman index, which is a measure of portfolio concentration. Such an index is built from portfolio weights and ranges from 0 (low concentration) to 1 (high concentration). Panel B shows no substantial difference in portfolio concentration among different ESG categories. In particular, all funds have on average a very small concentration index, meaning that they are well diversified independently form the ESG category. The distribution of funds capitalization (TNA value) is uniform across different ESG categories (Panel C). Independently from the category, funds' TNA ranges from 1 hundred thousand USD to more than 3 billions USD. Also in this case, distributions are leptokurtik and positively skewed. Distributions across ESG categories for the average daily returns over the last past year are described in Panel D. Consistent with Hong and Kacperczyk (2009) and the *responsibility effect* documented by Becchetti et al. (2018), average returns decrease monotonically as we move from Low to High ranked funds. High ESG ranked funds are less remunerative but also less risky than funds with a lower rating. Indeed, the minimum average return is the highest one for the High ESG ranked funds, while the standard deviation is the lowest one. Skewness is negative and very small for all categories, with the exception of the "Average" one showing a positive skewness. "Below Average" and "Average" funds have fat tails, while kurtosis is slightly higher than the normal for the other categories. The higher risk for Low ranked funds could be justified by their higher exposition to the stakeholder risk (Becchetti et al., 2018), to the crash-risk (Kim et al., 2014, Boubaker et al., 2020), market risk (Albuquerque et al., 2018) or to a combination of these risk sources.

Table III 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). Figures for volumes are in millions of traded shares. For any ESG category, the assets used to compute descriptive statistics are those where funds in that category invest in. Standard deviation of the returns and average trading volume are the only variables we need to compute the market depth for each asset as defined in (2). Table III shows that the assets in the investment universe of the High ranked funds are less risky than the assets in the other categories (Panel A). Reasonably, this outcome is consistent

Table III. Descriptive Statistics at Asset-level Across the ESG Categories

The table shows assets descriptive statistics across ESG categories for the standard deviation of daily returns over the last 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 where funds in that category invest in.

	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

with what we already know at fund level from Table II. Moreover, they have the highest trading volumes (Panel B). Hence, market depth from Equation (2) is higher for the assets held by the High ranked funds than for the other categories. The consequence of this finding is extremely relevant for our analysis, since the overlap between two funds, as given in Equation (5), is obtained by weighting the shared holdings by their assets market depth. Then, assets with a higher market depth provide a lower portfolio overlap, thus weakening the connections responsible for risk propagation.

Finally, we observe that market depth depends on a constant c, according to Formula (2). It is not that easy to calibrate such a constant. Different proposals are given in literature (see for example Cont and Wagalath, 2016, or Ellul et al., 2011). However, the uncertainty on the estimation of such a constant will impact on the results. To cross this problem, we fix arbitrarily c in such a way that the average vulnerability index of the High ranked funds is equal to 1. Then all the results have to be read in relative terms. Indeed we are interested in comparing the loss of market value experienced by the High ranked funds with that for the other ESG categories and the comparison does not depend on the constant c.

4.2 Network analysis

We consider a bipartite network with $N_F = 5625$ funds and $N_A = 19985$ assets. Funds in the network are rated for ESG according to five categories as explained in Section 4.1.

First, we compute the vulnerability index for each fund in the network as in Equation (7). Figure I shows the cross section average (upper panel) and standard deviation (lower panel) of the vulnerability index of the funds, across the different ESG categories. Figure I shows that funds

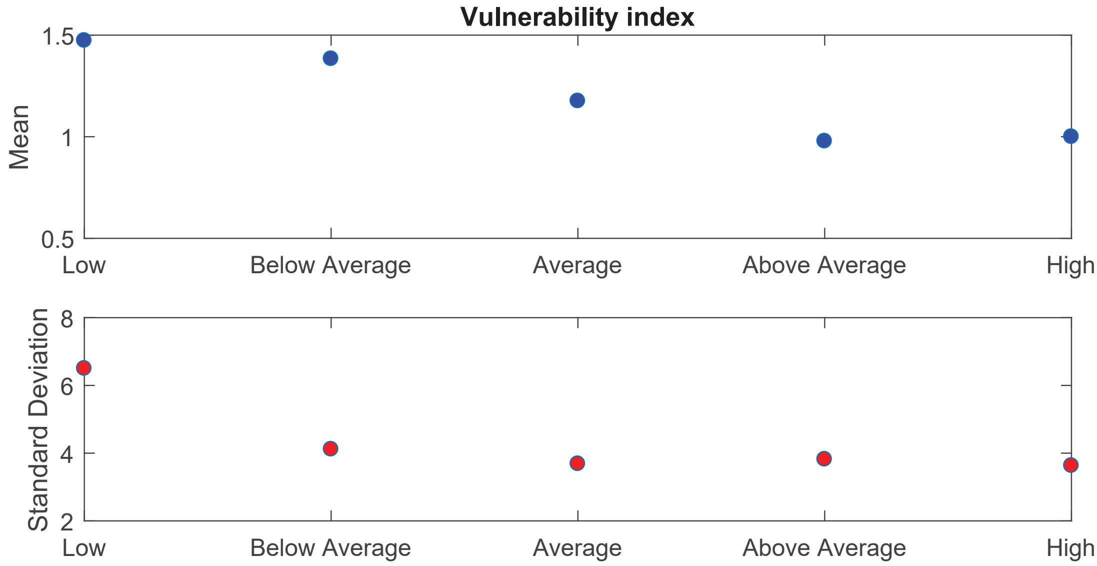

Figure I. Funds vulnerability index.

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.

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 which is almost the double as that for the High ranked funds. Such a result can justify why, during the last financial crisis and related liquidity shortage, ESG funds were able to mitigate their losses (Lins et al., 2017 and Nofsinger and Varma, 2014).

Figure II shows the relative loss of market value as given in Equation (9) for different fractions of assets liquidated by all the funds in the network and different ESG ratings: High ranked funds (crossed line) and Low ESG ranked funds (dotted line). We report only results for these two categories since they represent the extreme cases of our dataset and the difference in the level

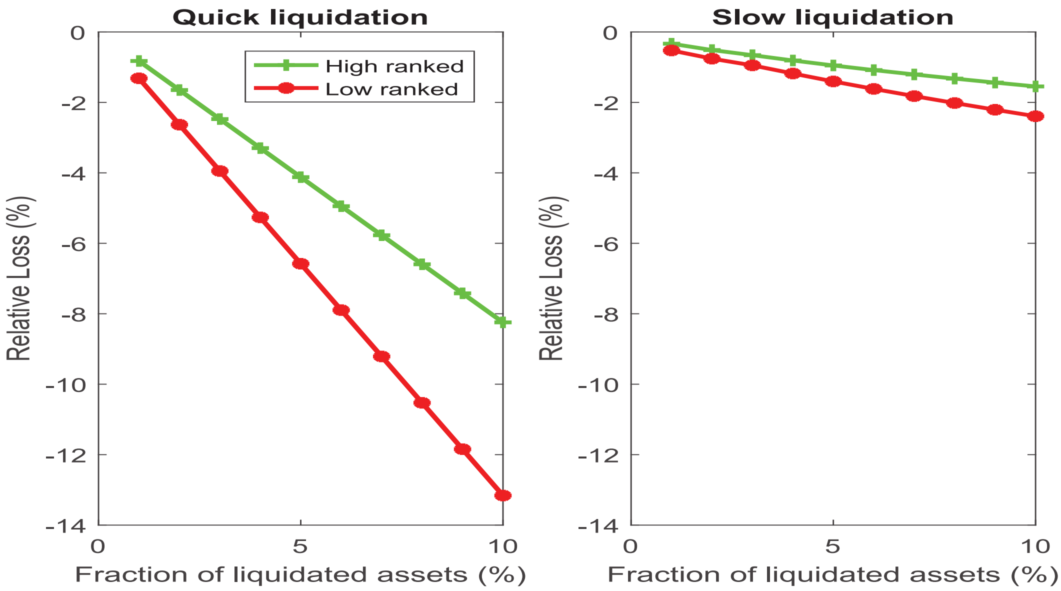

Figure II. Relative loss of market value.

The figure shows the relative loss, as given in Equation (9), 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 10 steps (right panel).

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 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 II shows that the Low ESG ranked funds lose 60% more that the High ESG ranked funds. Slower liquidation (right panel) has of course a weaker impact on the market value loss for both the Low ESG ranked and the High ESG ranked funds.

Contagion is less effective for the High ESG ranked funds. Indeed, the overlap of the High ranked funds with all the funds in the network, as measured by the elements of the adjacency matrix in (5), is lower than the overlap of Low ESG rated funds with all the funds in the network. This is shown in Figure III, where the highest thirty elements of the sub-adjacency matrix for the High ranked funds are compared with the highest thirty elements of sub-adjacency matrix for the Low ranked funds. The reduced overlap for the High ESG ranked funds follows from the fact they share the lower number of assets with the funds in the other categories, as it is shown in Table I. Such an effect is then amplified by the assets market depth. Any asset contributes to portfolio overlaps according to its market depth as in Equation (5). High ESG ranked funds invest in assets with higher market depths, having lower standard deviations of the returns and higher average trading volumes, as reported in Table III. As a result, the elements of the adjacency matrix for the High ESG ranked funds are lower than the elements of the adjacency matrix of the Low ESG ranked ones. Such a fact mitigates the risk of propagation of a local shock to the entire financial network.

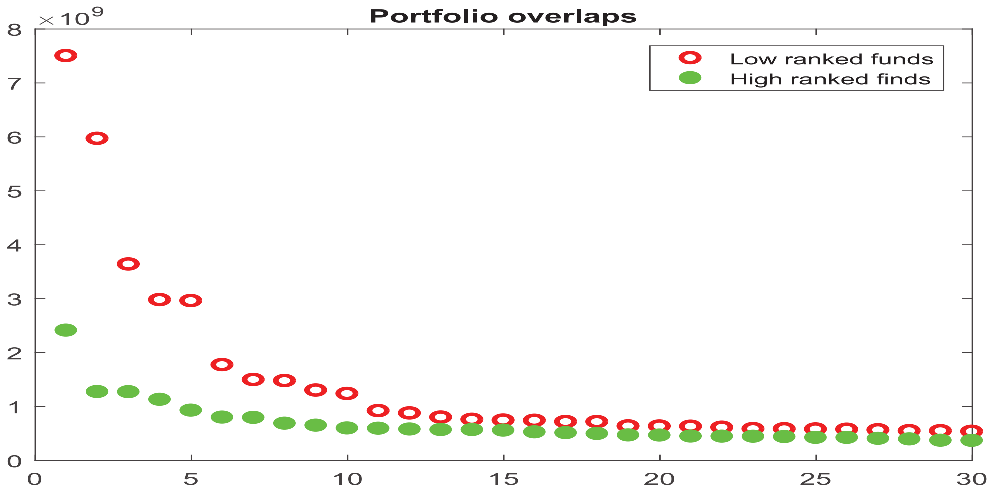

Figure III. Portfolio overlaps.

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.

5 Conclusions

Assets under management subject to ESG screening criteria has remarkably increased over time. Such a pattern could be the result of favorable risk/return characteristics offered by ESG investments, or the investors taste for such assets. After the Lehman Brothers filing for chapter 11, understanding the mechanisms behind contagion risk is one of the main concerns among policymakers. This paper is a first attempt to analyze ESG investing from a systemic point of view 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. To this aim, matching four datasets that contain granular information at fund and at holding level, we measure the level of interconnectedness of funds characterized by different ESG rates by computing the overlap between portfolios in terms of their assets in common. Assets in the overlap are weighted by their liquidity. Contagion from one fund to another is mediated by the overlap among the two portfolios.

Specifically, we examine a network of funds characterized by different levels of ESG compliance. First, we measure the vulnerability of any fund to contagion from other funds in the network. We find that the average of the vulnerability decreases with the level of ESG compliance. Second, for different levels of asset liquidation, we measure the market value that is lost by the funds because of fire-sales spillover. Results confirm that the loss is lower for the High ranked funds.

For the stability of the system, it is essential to gauge how ESG investing at fund-level translates into systemic risk. Consistently with the risk reduction effect documented in literature for single stocks or funds which are high ranked for ESG, investments with a higher level of ESG compliance are also less risky from a systemic point of view. In conclusions, our results indicate that contagion is less effective among funds with higher ESG rates. As such, investments with a higher level of ESG compliance appear to work as a shield in the case of a financial crisis by containing the losses.

References

Albuquerque R., Koskinen Y., and Zhang C. Corporate social responsibility and firm risk: Theory and empirical evidence. *Management Science*, 65(10), 2018.

Almgren R., Thum C., Hauptmann E., and Li H. Direct estimation of equity market impact. *Risk*, 18(7):57–62, 2005.

Amihud Y. Illiquidity and stock returns: cross-section and time-series effects. *Journal of Financial Markets*, 5(1):31 – 56, 2002.

Bauer R., Koedijk K., and Otten R. International evidence on ethical mutual fund performance and investment style. *Journal of Banking & Finance*, 29(7):1751–1767, 2005.

Bauer R., Otten R., and Rad A. Ethical investing in australia: Is there a financial penalty? *Pacific-Basin Finance Journal*, 14(1):33–48, 2006.

Bauer R., Derwall J., and Otten R. The ethical mutual fund performance debate: New evidence from canada. *Journal of Business Ethics*, 70(2):111–124, 2007.

Becchetti L., Ciciretti R., and Hasan I. Corporate social responsibility, stakeholder risk, and idiosyncratic volatility. *Journal of Corporate Finance*, 35:297–309, 2015.

Becchetti L., Ciciretti R., and Dalò A. Fishing the corporate social responsibility risk factors. *Journal of Financial Stability*, 37:25 – 48, 2018.

Benoit S., Colliard J. E., Hurlin C., and C. Pérignon C. Where the risks lie: A survey on systemic risk. *Review of Finance*, 21(1):109–152, 2017.

Bollen N. Mutual fund attributes and investor behavior. *Journal of Financial and Quantitative Analysis*, 42(3):683–708, 2007.

Boubaker S., Cellier A., Manita R., and Saeed A. Does corporate social responsibility reduce financial distress risk? *Economic Modelling*, 2020.

Braverman A. and Minca A. Networks of common asset holdings: aggregation and measures of vulnerability. *The Journal of Network Theory in Finance*, 4(3), 2018.

Chordia T., Goyal A., and Shanken J. Cross-sectional asset pricing with individual stocks: betas versus characteristics. *SSRN Working Paper No. 2549578*, 2017.

Ciciretti R., Daló A., and Dam L. The contributions of betas versus characteristics to the esg premium. *CEIS Working Paper No. 413*, 2019.

Cont R. and Schaanning E. Monitoring indirect contagion. *Journal of Banking & Finance*, 104: 85–102, 2019.

Cont R. and Wagalath L. Fire sales forensics: Measuring endogenous risk. *Mathematical Finance*, 26(4):835–866, 2016.

Corsi F., Lillo F., Pirino D., and Trapin L. Measuring the propagation of financial distress with granger-causality tail risk networks. *Journal of Financial Stability*, 38:18 – 36, 2018.

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

De Bandt O. and Hartmann P. Systemic risk in banking after the great financial crisis. In *The Oxford Handbook of Banking*. 2015.

El Ghoul S. and Karoui A. Does corporate social responsibility affect mutual fund performance and flows? *Journal of Banking & Finance*, 77:53–63, 2017.

Ellul A., Jotikasthira C., and Lundblad C. T. Regulatory pressure and fire sales in the corporate bond market. *Journal of Financial Economics*, 101(3):596 – 620, 2011.

Fama E. and French K. Disagreement, tastes, and asset prices. *Journal of Financial Economics*, 83 (3):667–689, 2007.

Fink K., Krüger U., Meller B., and Wong L.-H. The credit quality channel: Modeling contagion in the interbank market. *Journal of Financial Stability*, 25:83 – 97, 2016.

Flori A., Lillo F., Pammolli F., and Spelta A. Better to stay apart: asset commonality, bipartite network centrality, and investment strategies. *Annals of Operations Research*, 2019.

Galema R., Plantinga A., and Scholtens B. The stocks at stake: Return and risk in socially responsible investment. *Journal of Banking & Finance*, 32(12):2646–2654, 2008.

Global Sustainable Investment Alliance. Global sustainable investment review. Technical report, 2016.

Global Sustainable Investment Alliance. Global sustainable investment review. Technical report, 2018.

Glushkov D. and Statman M. The wages of social responsibility. *Financial Analysts Journal*, 65 (4):33–46, 2009.

Guo W., Minca A., and Wang L. The topology of overlapping portfolio networks. *Statistics & Risk Modeling*, 33(3-4):139–155, 2016.

Heinkel R., Kraus A., and Zechner J. The effect of green investment on corporate behavior. *Journal of financial and quantitative analysis*, 36(4):431–449, 2001.

Herzel S., Nicolosi M., and Stărică C. The cost of sustainability in optimal portfolio decisions. *The European Journal of Finance*, 18(3-4):333–349, 2012.

Hong H. and Kacperczyk M. The price of sin: The effects of social norms on markets. *Journal of Financial Economics*, 93(1):15–36, 2009.

Joliet R. and Titova Y. Equity sri funds vacillate between ethics and money: An analysis of the funds' stock holding decisions. *Journal of Banking & Finance*, 97:70–86, 2018.

Kanno M. Assessing systemic risk using interbank exposures in the global banking system. *Journal of Financial Stability*, 20:105 – 130, 2015.

Kempf A. and Osthoff P. The effect of socially responsible investing on portfolio performance. *European Financial Management*, 13(5):908–922, 2007.

Kim Y., Li H., and Li S. Corporate social responsibility and stock price crash risk. *Journal of Banking & Finance*, 43:1–13, 2014.

Kyle A. S. Continuous auctions and insider trading. *Econometrica*, 53(6):1315–1335, 1985.

Lins K. V., Servaes H., and Tamayo A. Social capital, trust, and firm performance: The value of corporate social responsibility during the financial crisis. *The Journal of Finance*, 72(4):1785–1824, 2017.

Luo A. and Balvers R. Social screens and systematic investor boycott risk. *Journal of Financial and Quantitative Analysis*, 52(1):365–399, 2017.

Merton R. C. A simple model of capital market equilibrium with incomplete information. *The Journal of Finance*, 42(3):483–510, 1987.

Nicolosi M., Grassi S., and Stanghellini E. Item response models to measure corporate social responsibility. *Applied Financial Economics*, 24(22):1449–1464, 2014.

Nofsinger J. and Varma A. Socially responsible funds and market crises. *Journal of Banking & Finance*, 48:180–193, 2014.

Pastor L., Stambaugh R., and Taylor L. A. Sustainable investing in equilibrium. *NBER Working Paper No. 26549*, 2019.

Patel S. and Sarkissian S. To group or not to group? evidence from mutual fund databases. *Journal of Financial and Quantitative Analysis*, 52(5):1989–2021, 2017.

Pedersen L. H., Fitzgibbons S., and Pomorski L. Responsible investing: The esg-efficient frontier. *SSRN Working Paper No. 3466417*, 2019.

Renneboog L., Horst J. T., and Zhang C. The price of ethics and stakeholder governance: The performance of socially responsible mutual funds. *Journal of Corporate Finance*, 14(3):302–322, 2008.

US Social Investment Foundation. The impact of sustainable and responsible investment. Technical report, 2016.

US Social Investment Foundation. The impact of sustainable and responsible investment. Technical report, 2018.

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