Clusters of social impact firms: A complex network approach

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Abstract

With increasing interest around social impact investments, there is a pressing need to properly define the universe of social impact targets. This paper aims to identify communities of social impact firms (SIFs) ranked in terms of their compliance with the OECD criteria for impact investing. We include in the analysis the network dimension of the firms. Specifically, we assume that SIFs represent the nodes of a weighted complex network, whose weights grow when the linked nodes show similar behaviors in pursuing social impact targets. To empirically validate our model, we used a novel hand-collected dataset of SIFs across multiple countries. Our results highlight that the economic sector and country of origin do not act as a distinguishing factor among SIF communities. However, firm size seems to matter as firms which are more compliant with the social impact criteria tend to be smaller.

Keywords: Social impact finance, networks, clustering coefficient.

1. Introduction

Socially responsible investments (SRIs) are topical concerns in academic studies, economic practice, and policy makers (GSIA, 2021; Höchstädter and Scheck, 2015; O'Donohoe et al., 2010). However, a new wave of social-oriented investments, i.e. social impact investments (SIIs), has emerged, and it goes well beyond the traditional approaches of ethical or socially responsible finance. While SRIs integrate environmental, social, and governance factors (so called ESG factors) into the investment decision-making process, SIIs intentionally address one or more social and environmental issues in order to make a positive and measurable impact as well as a financial return. Therefore, the distinctive characteristics of SIIs are the explicit purpose of generating a positive social impact and the measurability of social and environmental outcomes, alongside financial returns (O'Donohoe et al., 2010; OECD, 2015; Caseau and Grolleau, 2020).

The social impact investing market is growing rapidly (GSIA, 2021; OECD, 2019) and is attracting many institutional investors, asset managers and multinational firms. Indeed, in 2020 the Global Impact Investing Network (GIIN)'s Impact Investor Survey[1] accounted for 294 professional investors that collectively manage USD 404 billion of impact investing assets, which represents a significant increase compared to the 64 investors that began making impact investments before 2000. Remarkably, almost 40% of survey respondents are organizations that usually operate in traditional markets; this suggests that social impact investments are not targeted exclusively by dedicated investors.

[1] The GIIN 2020 survey included questions on respondents' impact investing activity during 2019. To ensure that respondents have meaningful experience with impact investing, responding organizations either (1) manage at least USD 10 million in impact investing assets and/or (2) have made at least five impact investments. The respondents are headquartered in 46 different countries, 77% of them are located in developed markets. In terms of the geographic allocation of assets, almost 50% of respondents invest primarily in developed markets. Approximately two-thirds (65%) of respondents are asset managers (either for profit or non-profit).

As the demand from involvement of large-scale investment firms grows, there is an increasing need to identify the main structure and potential of this emerging market. According to OECD (2015), the main components of the social impact investment ecosystem can be traced back to three areas: (i) SII demand-side, that includes social needs and social service providers; (ii) SII supply-side, as derived from the pools of capital and investors; and finally (iii) the SII intermediaries, which includes financial transactions and financing instruments. Some studies have recently analyzed the financial properties of both the supply-side and intermediaries of SII, such as social impact venture capital and growth funds (Grey et al., 2015; Barber et al., 2021; Jeffers et al., 2021; Gezcy et al., 2021). Nevertheless, there is still a lack of clarity regarding the definition of the potential extent of the SII targets (i.e. the demand-side). However, it is increasingly important for investors to be able to delimit the broad universe of social impact firms (SIFs) and to classify each SIF within their community. In the spirit of the rating approach already applied by Halbritter and Dorfletner (2015) in the SRIs market, we believe that this will foster the acknowledgement of SIFs as a distinct asset class and, more importantly, will allow the potential investors to identify the communities of prospective target firms (OECD, 2019).

In this paper, we contribute to fill this gap by developing a theoretical model based on complex network theory (see e.g. Vega-Redondo, 2007) that allows us to understand the structure of the social impact firms (SIFs) market. To identify communities of SIFs, we take into account the interconnection structure among such firms, so that SIFs are highly interconnected when they are very similar in terms of their social impact behaviour. In our model, SIFs are the nodes of a weighted network, whose connections depend on the degree of compliance of each firm to several SII criteria. In doing so, we are in line with some authoritative contributions (see the related discussion in Section 3). As regards the methodological instruments, we implement an optimal clustering procedure of the firms through the clustering coefficients of the related nodes, which are computed according to the definition of Onnela et al. (2005).

To empirically validate our model we rely on the OECD (2015) eligibility criteria to identify a SIF. In fact, in 2013 the Social Impact Investment Taskforce - established by the G8 - asked the OECD to provide a framework to build the evidence base of the SII field, and to produce a report on the market. Therefore, we construct a novel hand-collected dataset of SIFs across multiple countries that allows the measuring for each firm of the degree of compliance to the SIF definition provided by the OECD (i.e. SIF compliance score). It follows that in our model, firms connect in the network by the degree of compliance to the SIF definition provided by the OECD (i.e. SIF compliance score).

Our results suggest that firms are more likely to be clustered when referring to the local perspective of the Euclidean distance rather than the global context of the Shannon entropy. This evidence suggests that the individual features of each firm are more relevant than the properties of the set of the firms as a whole.

Furthermore, when the connections of the firms are analyzed based on the level of the SIF compliance score, we obtain two quite balanced clusters of firms with low (46 firms) and high (73 firms) community structure. The analysis of the economic sectors and countries within these two clusters outlines a rather homogeneous scenario, suggesting that sector and country do not act as a differentiator in the level of the SIF compliance score. Some differences are found instead in terms of firm size, that is, firms with higher values of the SIF compliance score appear to be smaller than firms with lower values of the SIF compliance score in the most recent years.

Our paper contributes to the finance literature in several ways. First, we focus on the public equity impact investing market, whose structure is, to our knowledge, unexplored by the existing literature[2]. However, public equity at-

[2]Practitioners seem fully aware of the relevance to better investigate SIIs in the public markets. For example, MSCI ESG Research has developed new tools to help institutional investors manage their exposure to impact themes across public equity allocation, by reporting that "We have found that some institutional investors increasingly seek to apply an "impact lens" across asset classes – aiming to activate public equity and public debt portfolios towards sustainable solutions and environmental challenges". See Menou and Nishikawa (2016), p. 6. Also, JP Morgan reports that "We expect more publicly traded investment opportunities will

tracts the second largest allocation of Asset Under Management of the GIIN's 2020 Impact Investor Survey respondents.

In addition, we provide new evidence on impact investing from a different angle compared to traditional approaches that look primarily at firm characteristics. Instead, we focus on the overall structure of the market by exploiting the connections among firms using a complex network approach. Indeed, our paper is close to a wide strand of literature dealing with communities of firms under a complex network analysis, in the specific context of clustering coefficients. However, the analysis of firms in the impact investing market is neglected by this stream of literature.

Finally, we believe that our findings are relevant for investors and asset managers to detect possible patterns in the identification of SIFs for their impact equity portfolio in order to better assess opportunities in this market. Additionally, our results are relevant both for investors and firms governance, since they contribute to the debate on the absence of a trade-off between high level of impact and profitability.

The rest of the paper is organized as follows. In Section 2, we offer a review of the main financial and network literature related to our study. In Section 3, we outline the theoretical complex network model for describing the universe of the social impact targeted firms. In Section 4, we present the details of the methodologies employed for the communities' assessment problem. We present the data in Section 5 and results in Section 6. Concluding remarks can be found in Section 7.

2. Literature review

Impact investing represents an advanced stage of sustainable investing different from the more traditional SRIs. While SRIs typically focus on reducing companies' and investors' risks by assessing companies' non-financial perfor-

emerge as the market matures". See O'Donohoe et al. (2010), p.14.

mance on the basis of environmental, social and governance (ESG) criteria, impact investing focuses on core businesses and the products and services these companies produce. According to this perspective, impact investing aims to positively impact society beyond ESG-related compliance by looking for companies that directly contribute to solve a social and/or environmental issue and by measuring the impact generated (GIIN)[3].

A growing range of actors are emerging in the social impact investment market to form an ecosystem consisting of investors, social impact ventures and intermediaries (OECD, 2015). Since the emergence of the impact investing concept, this ecosystem has expanded and become more complex. As a result, a more comprehensive picture of the SII market requires an assessment of the different components of the market. Thus far, financial literature has mainly focused on SII intermediaries and investors, by investigating the financial properties of the major impact investing vehicles (i.e. the supply-side). For instance, Barber et al. (2021) focus on impact funds and show that impact-oriented investors are willing to accept lower returns, reflecting investors' varying objectives and ability to balance financial returns and impact goals. Similarly, Jeffers et al. (2021) observe that impact funds underperform the public market, while being less sensitive to movements in public equity markets relative to comparable investment vehicles. Geczy et al. (2021) analyze legal documents struck by impact funds to analyse the effect of impact on contracting choices of funds. However, a key element that drives impact investing transactions is the identification of the social delivery organizations that represent the final destination of the impact investment resources (i.e. the demand-side). Social delivery organizations can take on multiple forms. Among existing social delivery organizations, the Social Impact Investment Taskforce defines SIFs as profit-with-purpose businesses that include a social mission in their core business model (SIIT, 2014). Even though some steps forward have been made to build a uniform definition of social impact targets (see OECD, 2015), lack of clarity still exists regarding the

[3]https://thegiin.org/impact-investing/need-to-know/#what-is-impact-investing

existing population of SIFs that could potentially be addressed by SII investees, especially in the public equity market.

Social network analysis provides useful tools to carry out such investigation. In particular, the clustering coefficient explores the entity of the mutual interconnections of the firms which are connected with a given one, hence providing a quantitative dimension of the cohesiveness of the surrounding environment. In this respect, and just to cite a few, Han et al. (2009) deal with the empirical analysis of the airline companies by assessing the hierarchy of their interconnections and their community structure through a clustering coefficient-based analysis. In a different context, Sankar et al. (2015) use the clustering coefficient to show the presence of a small world structure when clustering companies in the corporate Indian area. Under an evolutive perspective, Li et al. (2016) use the clustering coefficient to describe the changing of the community structure of a network of companies belonging to the Chinese market.

In the specific field of SRIs and CSR, Afonso et al. (2012) apply a clusters analysis approach to group Portuguese companies, and their findings show that companies that had a better social performance are not the ones who had a better economic performance. Jamali et al. (2009) obtain insights into managerial perspectives of CSR using quick cluster analysis and provide evidence of some commonalities in CSR orientations among three Middle Eastern countries. Similarly, Ortas et al. (2015) investigate the role of social, cultural, legal, regulatory and economic differences between specific countries in determining how companies committed to a specific voluntary CSR, by comparing firms in Spain, France and Japan, and reveal two clusters of companies behaving in different ways with regard to sustainability issues. Jitmaneeroj (2016) examines the relationship between overall ESG score and each ESG factor by using a three-stage integrative methodology that involves cluster analysis as well. Thanks to the clustering method, they are able to pinpoint social performance as the most critical component for the majority of industries, followed by environmental performance.

Grounded on the streams of literature discussed above, our paper applies the complex network approach to map the community structure of the emerging, and so far neglected, market of SIFs.

3. The social impact financial network model

Here we present the financial network model we considered in our analysis. For an overview of complex network theory, we refer to the complete dissertation in the monograph by Newman (2018). We also mention Cardarelli (2007) and Kalyagin et al. (2014) for a discussion of the financial applications of complex networks.

The set V collects n social impact targeted firms, according to the definition provided by OECD (2015). The generic firm will be labeled by $i, j, k = 1, \dots, n$.

We are here interested in the measure of the social impact compliance of the individual firms. The measure of the social impact compliance of firm i will be denoted by μ_i. Without loss of generality, we normalize such measures, so that $\mu_i \in [0, 1]$ for each $i = 1, \dots, n$. See the next section for the definition of the μ's under the point of view of the empirical analysis.

To construct the weights of the network, we assume that the entity of the connection between two firms is driven by their social impact compliance measures. In particular, we consider that two firms are highly connected when the measures of their social impact compliance score exhibit similar and large values. In so doing, we are in line with the aknowledged property of the link formation process, so that nodes with similar characteristics tend to link to each other (on this, see the breakthrough paper by Park and Barabasi, 2007). In the specific financial case, this assumption is grounded on the evidence that behaviors of ethical nature – like being compliant with social impact targets – cluster the considered agents, so that similar high-level targets are associated to a high degree of closeness. In this respect, we mention the important contribution of Brass et al. (1998), where the authors describe in detail how similar unethical behaviors drive the strength of the interactions of a group of individuals, by offering also a literature review on the topic. Thus, the construction of the weight of the edge connecting two different nodes i and j, namely w_{ij}, can be formalized by a convex combination of two criteria as follows:

$$w_{ij} = \alpha f(|\mu_i - \mu_j|) + (1-\alpha) g(\mu_i, \mu_j), \qquad i \neq j, \tag{1}$$

where $\alpha \in [0,1]$, $f : [0,1] \to [0,1]$ is a decreasing function such that $f(0) = 1$ and $f(1) = 0$ while $g : [0,1]^2 \to [0,1]$ is an increasing function with respect to its components such that $g(0,0) = 0$ and $g(1,1) = 1$.

We also impose $w_{ij} = 0$ when $i = j$, to exclude the not interesting case of self-connections of firms.

Some comments on the definition of the weights are required.

The term $f(|\mu_i - \mu_j|)$ represents the contribution to the weights due to the distance between the social impact compliance measures of firms i and j. We are assuming that the measure of the social impact compliance contributes to classify the firms of V and to state their mutual relationships, so that high (low, resp.) similarities of the measures leads to strongly (weakly, resp.) connected firms. The intuition behind this assumption lies in the evidence that agents feel more connected with their similars, where similarity is here intended as analogous entity of social impact. The corner cases capture the idea that maximum (minimum, resp.) distance between μ_i and μ_j means minimum (maximum, resp.) possible similarity contribution to the level of connection between two firms. We will refer hereafter to function f as the (social impact) *similarity term* of the weights.

The term $g(\mu_i, \mu_j)$ penalizes low values of the social impact compliance measure and promotes high ones when stating the relationships between the firms. Such a quantity is conceptualized to model that the firms with relevant social impact compliance tscores should be highly interconnected. The ground of this assumption is that the firms with a remarkable social impact compliance – the *leaders* – play the social role of being an illustrative example for the other firms – the *followers*. The strength of the connection is more evident when also the followers have a high measure of their SIF score. The corner cases describe the extreme situations of no social impact compliance and full social impact compliance of both firms i and j, which gives absence of a contribution of this term to connection and maximum one, respectively. We will refer to function g as the (social impact) *value term* of the weights.

The parameter α represents the balance between similarity and value terms. As α grows, then the relevance of the social impact value in building the weights decreases while the one of the similarity term grows. In the extreme cases, we have full value-based weights ($\alpha = 0$) and similarity-based ones ($\alpha = 1$).

By definition, $w_{ij} \in [0,1]$, for each $i, j = 1, \ldots, n$. We collect all the w's in a n-squared matrix $\mathbf{W} = (w_{ij} : i, j = 1, \ldots, n)$, which can be viewed as the weighted adjacency matrix of a network whose nodes are the elements of V. Thus, we have a network $\mathbf{N} = (V, \mathbf{W})$.

Since all the considered firms are social impact targeted, then network $\mathbf{N}$ is complete by construction.

4. Methodology for communities assessment

The nodes of the network $\mathbf{N}$ can be clustered in non overlapping clusters. This section is devoted to the construction of different theoretical optimization models for their assessment and comparison.

4.1. Basic concepts and an illustrative example

We will refer hereafter to two different concepts of *communities*. One of them refers to the community structures around the individual nodes of the network; the other one refers to the clusters of the nodes of the network, hence pointing to a more global level. In order to avoid misunderstanding, we will point to the former concept as communities or *community structures* and to the latter one as *clusters*.

The concept of cluster is based on the likelihood of the nodes in terms of their community structures as social impact targeted firms. At this aim, we proceed by employing the weighted clustering coefficient of the network.

We adopt the definition provided by Onnela et al. (2005), so that the clustering coefficient of the node $i \in V$ is given by

$$\tilde{c}_i = \frac{\sum_{j,k \in V} (w_{ij}^{1/3} w_{ik}^{1/3} w_{jk}^{1/3})}{(n-1)(n-2)}. \tag{2}$$

The clustering coefficients in (2) will be collected in a vector $\mathbf{c} = (c_1, \ldots, c_n)$. As complex network theory and formula (2) suggest, the clustering coefficient of a node i represents a quantification of the community structure around i. As we will see soon, they are assumed to induce clusters in the set V, in the sense that nodes with similar communities will be lumped together to form clusters. Such clusters will be collected in a suitably defined partition of V. Before providing a formal definition of cluster, we firstly describe the rationale behind the proposed conceptualization through an illustrative example.

Example 4.1. *Consider* $V = \{1, 2, 3, 4\}$ *and a weighted adjacency matrix*

$$\mathbf{W} = \begin{pmatrix} 0 & 0.9 & 0.9 & 0.01 \\ 0.9 & 0 & 0.2 & 0.01 \\ 0.9 & 0.2 & 0 & 0.01 \\ 0.01 & 0.01 & 0.01 & 0 \end{pmatrix}$$

The clustering coefficients of the nodes can be computed on the basis of formula (2). They are $\mathbf{c} = (0.1058, 0.1028, 0.1028, 0.0195)$.

Intuition suggests that nodes 1,2,3 exhibit very similar values of the clustering coefficient. Hence, they seems to form a cluster of nodes sharing similar characteristics in terms of their social impact measures. Node 4 is far away from the others as concerns the clustering coefficient, and it forms a cluster by itself.

We can say more than this. If we wish to be particularly restrictive when defining the criterion to be applied for nodes belonging to clusters – like saying that two nodes belong to the same cluster when they have an identical clustering coefficient – we observe three clusters in V*:* $\{1\}, \{2, 3\}, \{4\}$.

Even differently, we can imagine that two nodes belong to the same cluster *when their clustering coefficients differ for less than 0.5. In this case, all the nodes of V belong to the same cluster, V itself.*

Example 4.1 highlights that clusters can be identified according to two main strategies. First of all, the values of the clustering coefficients have to be compared as ordered numbers; thus, their ranking is required. Second, an *a-priori* criterion for determining the clusters in the set of the nodes has to be identified.

Importantly, the identification of the clusters requires the knowledge of the order of the clustering coefficients. In this respect, we notice that an order statistics easily allows the ranking of the nodes in increasing – or decreasing – order with respect to the related clustering coefficient. In particular, we can write the vector $\mathbf{c}^{ord}$ of the ordered clustering coefficient as $\mathbf{c}^{ord} = \big(c_{(1)}, \ldots, c_{(n)}\big)$, where $\{(1), \ldots, (n)\}$ is the order of V such that

$$c_{(1)} \leq \ldots \leq c_{(n)}.$$

Without loss of generality and for the sake of notation, we can assign the labels of the firms in V in order to have $c_{(i)} = c_i$, for each $i \in V$; thus,

$$c_1 \leq \ldots \leq c_n.$$

4.2. Clusters assessment: the optimization models

We now propose a set of optimization models for the identification of the *optimal* partition of the set V under different contexts.

To proceed, we identify the generic element $i \in V$ with its clustering coefficient c_i, so that a partition of V can be identified with a partition of the components of the vector $\mathbf{c}$. Reasonably, we restrict the analysis to partitions satisfying a contiguity condition, according to the following

Definition 4.2. *Given an integer $K \in \{1, \ldots, n\}$, a* contiguos partition with cardinality K *– i.e.: a partition of the components of* $\mathbf{c}$ *with cardinality K and fulfilling a contiguity condition – is a set $\pi(K) = \{\pi_1, \ldots, \pi_K\}$ such that $\pi_j \subset \{c_1, \ldots, c_n\}$, for each j; $\pi_i \cap \pi_j = \emptyset$, for each $i \neq j$; $\pi_1 \cup \ldots \cup \pi_K = \{c_1, \ldots, c_n\}$*

and the contiguity condition *holds, i.e:*

$$c_i \in \pi_k \text{ and } \mathrm{c_j} \in \pi_{\mathrm{k+1}} \text{ implies } \mathrm{c_i} < \mathrm{c_j}, \qquad \forall \mathrm{k}. \tag{3}$$

We collect all the contiguos partitions with cardinality K in a set $\Pi^{(K)}$.

As preannounced above, definition 4.2 provides also a partition of the set V. Indeed, by using a reasonable abuse of notation, we can say that $\pi_j \subset V$, for each j; $\pi_i \cap \pi_j = \emptyset$, for each $i \neq j$; $\pi_1 \cup \ldots \cup \pi_K = V$ and the contiguos condition in (3) is rewritten by replacing c_i, c_j with i, j, respectively.

The contiguity condition (3) suggests that a contiguos partition of V, namely $\pi(K) = \{\pi_1, \ldots, \pi_K\} \in \Pi^{(K)}$, is fully identified by some *internal corner points* $i_1, \ldots i_{K-1} \in V$, which are implicitly defined as follows:

$$\pi_k = \{i_{k-1} + 1, \ldots, i_k\}, \qquad k = 1, \ldots, K, \tag{4}$$

with the conventional agreement $i_0 = 1$ and $i_K = n$.

The optimality criteria employed for detecting the clusters in V is grounded on the similarity between the distribution $\mathbf{P} = (p_1, \ldots, p_n)$ induced by normalizing the elements of $\{c_1, \ldots, c_n\}$ and a properly weighted distribution $\mathbf{Q}^{(\pi(K))} = (q_1^{(\pi(K))}, \ldots, q_K(\pi(K)))$ of the partition $\pi(K) = \{\pi_1, \ldots, \pi_K\} \in \Pi^{(K)}$ defined as in (4). Specifically, we define

$$p_i = \frac{c_i}{\sum_{j=1}^n c_j}, \qquad \forall\, i \in V;$$

$$q_k^{(\pi(K))} = \frac{\sum_{j=i_{k-1}+1}^{i_k} c_j}{\sum_{j=1}^n c_j}, \qquad \forall\, k \in \{1, \ldots, K\}.$$

In general, $K < n$. Thus, in order to provide more insights from the optimization procedures, the distributions $\mathbf{Q}^{(\pi(K))}$ is transformed in a new distribution, namely $\mathbf{P}^{(\pi(K))} = (p_1^{(\pi(K))}, \ldots, p_n^{(\pi(K))})$, with support given by all the nodes of the network as follows

$$p_i^{(\pi(K))} = \frac{q_k^{(\pi(K))}}{|\pi_k|} \cdot \mathbf{1}_{\{i \in \pi_k\}}, \qquad \forall\, i \in V,$$

where $\mathbf{1}_A$ is the indicator function of the set A.

The probability distribution defined in $\mathbf{P}^{(\pi(K))}$ is obtained by firstly taking the clusters π's according to $\mathbf{Q}^{(\pi(K))}$, and then by taking randomly the individual node within the cluster.

Two optimization problems are presented.

Problem $\mathcal{P}_H$. Find $(K^\star, \pi^\star(K^\star))$, where $\pi^\star(K) = \{\pi_1^\star, \dots, \pi_K^\star\} \in \Pi^{(K)}$, solving the following problem:

$$\min_{K \in \{1,\dots,n\}} \min_{\pi(K) \in \Pi^{(K)}} H(\mathbf{P}; \mathbf{P}^{(\pi(K))}),$$

where

$$H(\mathbf{P}; \mathbf{P}^{(\pi(K))}) = \Big| \sum_{j=1}^{n} p_j \ln p_j - \sum_{j=1}^{n} p_j^{(\pi(K))} \ln p_j^{(\pi(K))} \Big|$$

is the distance between the Shannon entropies of the distributions $\mathbf{P}$ and $\mathbf{P}^{(\pi(K))}$.

Problem $\mathcal{P}_E$. Find $(K^\star, \pi^\star(K^\star))$, where $\pi^\star(K) = \{\pi_1^\star, \dots, \pi_K^\star\} \in \Pi^{(K)}$, solving the following problem:

$$\min_{K \in \{1,\dots,n\}} \min_{\pi(K) \in \Pi^{(K)}} E(\mathbf{P}; \mathbf{P}^{(\pi(K))}),$$

where

$$E(\mathbf{P}; \mathbf{P}^{(\pi(K))}) = \frac{1}{n} \sum_{j=1}^{n} (p_j - p_j^{(\pi(K))})^2$$

is the Euclidean distance between the distributions $\mathbf{P}$ and $\mathbf{P}^{(\pi(K))}$.

Both problems $\mathcal{P}_H$ and $\mathcal{P}_E$ admit solution, since the admissible region is discrete and finite. They share the same criterion of minimizing the distance between the distributions $\mathbf{P}$ and $\mathbf{P}^{(\pi(K))}$. However, their informative content is radically different. Indeed, problem $\mathcal{P}_H$ involves an entropy measure. Thus, the concept of closeness has to be intended in the sense of the disorder of the distribution. In particular, the Shannon entropy of a distribution increases as the distribution is closer to the uniform case, while it decreases when the considered distribution approaches the pure polarization case of a Dirac function over one of the nodes. Therefore, problem $\mathcal{P}_H$ is solved by the partition leading to the best approximation of the shapes of $\mathbf{P}$ and $\mathbf{P}^{(\pi(K))}$. Differently, problem $\mathcal{P}_E$ involves the Euclidean distance. In this case, the closeness is meant to be associated to the average distance between the probabilities of the individual nodes.

5. Data and sample description

Since the market of SIIs is relatively recent, data on social impact targets is lacking[4]. Therefore, we create a unique hand-collected dataset by starting out with the full list of firms reported on the website wikipositive.org, a public portal that builds and shares a list of private and public enterprises that (to some degree) meet high financial, social, and environmental standards. As of the end of 2018, the platform included slightly more than 1000 firms from different geographical areas.

Given the abovementioned list of firms, we first require firms to be publicly traded. Then, we rely on an independent and publicly available framework provided by OECD (2015) to identify whether a listed firm might or might not be considered a SIF. The advantage of using this framework is threefold. First, it is not based on a broad assessment of SII scope and operations but it provides a detailed list of the core characteristics of a transaction to be classified as SII. Moreover, the OECD (2015) definition clearly draws the eligibility boundaries for each of the core characteristics of SII, therefore, helping to operationalize the SIF definition during the data collection process. Finally, this framework has already been validated by other studies, in particular by La Torre and Chiappini

[4]There are not publicly available datasets that provide both a classification of firms as SIF and a measure of the extent to which a firm is conducting its business operations in a social impact manner. Some datasets (e.g., Asset4, KLD, and CSRHUB) provide Environmental Social and Governance (ESG) scores, which allow assessing to what extent a firm incorporates ESG criteria into their business activity. However, this is quite different from our analysis scope because ESG scores are available regardless of the firm's mission. Indeed, a great majority of firms that have a high ESG score do not have a social mission as their core business.

(2016) and Chiappini (2017) for a sample of microfinance vehicles and social impact funds, and by Biasin et al. (2019) for macro asset allocation purposes. According to the OECD (2015), SIFs should declare a corporate mission that could potentially fit some specific social impact areas (i.e. SII areas criterion). In particular, the OECD identifies eight core SII areas that can be eligible: ageing, disability, health, children and families, public order and safety, affordable housing, unemployment, and education and training. In addition, other areas are leaning towards the core areas and can be considered social impact areas if they benefit a population at risk. Among those areas, there is agriculture, environment and energy, water and sanitation, financial services (including microfinance), and Information and Communications Technology (ICT).

After we screen our initial sample with this first criterion, which we indicate as a social impact target, we end up with 130 international listed firms with potential as a SIF. However, as indicated in the OECD (2015), the firm's declared social mission is not sufficient to identify a SIF. The following four additional criteria are also required to identify an impact investee profile[5]:

(1) Beneficiary context: it relates to who benefits from the firm's operations, typically populations at risk or those living in underserved or developing areas.

(2) Degree of publicness: it relates to the type of good or service provided by the firm that should be neither pure private nor pure public, not completely excluding benefits accruing to non-target beneficiaries.

(3) Delivery organization intent: it deals with a verifiable demonstration of the firm's social intent and commitment to the social cause. Some form of

[5]Note that in the OECD (2015) definition the unit of assessment is the SII transaction. Therefore, the proposed definition includes a list of characteristics for both sides of the transaction (the demand and the supply-side). As clearly stated by OECD (2015), p. 44, two of these features refer to the supply-side of the transaction (i.e. investor intent and return expectations), for this reason they are excluded from our analysis that conversely focuses on the demand side (SIFs).

compulsory report- ing of social outcomes to shareholders within the organization's statutes, external certification, or legally binding constraints could provide a clear indication of a com- mitment to social goals.

(4) Measurability of social impact: it refers to the fact that a firm has to somehow measure the social impact generated in order to be a valuable target of a SII. The assessment of the social impact generated can be qualitative or quantitative.

We use several sources of data to verify whether each firm is compliant with each criterion. From each firm's webpage, we analyze the firm's overview, mission, article of association, and financial statements in order to clearly identify the kind of beneficiaries, the degree of publicness, and the social delivery organization intent. More precisely, we analyze the delivery intent of the firm by further requiring that the firm has one of the following: (i) a sustainability report; (ii) an external certification or label, or (iii) legally binding constraints within the article of association. Finally, we use sustainability reports retrieved from the firm's webpage to investigate the effective measurement of the firms' social impact. Specifically, we require that each firm disclosed at least for two years a sustainability report and that each of them includes a measure (i.e., figures or absolute amounts) of the actual social impact of the firm's projects.

We further rank each firm on the basis of the number of social impact criteria that they meet, which represents the degree of compliance of each firm to the OECD definition of SII (i.e. SIF compliance score). In doing so, we define μ_j – introduced in Section 3 – as the percentage of the social impact criteria met by firm j over the possible maximum amount, which is five. Thus, $\mu_j \in [0, 1]$, for each firm j. The measure of the social impact compliance of each firm – i.e, the SIF compliance score – is therefore expressed on a scale from 1 (only the SII areas criterion is met) to 5 (all the OECD eligibility criteria are met). The higher the SIF compliance score, the closer is the activity carried out by the firm to the social impact definition provided by OECD (2015), which in turn would imply a higher likelihood of being eligible for investment in a social

Table 1: Social target areas. The table reports the SII Areas, with related number of firms and percentages.

SII Areas	**Number**	**Percentages**
Environment and energy	67	56.3%
Health	21	17.65%
Agriculture	9	7.56%
Water and sanitation	8	6.72%
ICT	6	5.04%
Financial services	4	3.36%
Education and training	2	1.68%
Housing	2	1.68%
TOTAL	119	100.00%

impact portfolios.

At the end of the described procedure, we classify 119 firms based on their SIF compliance score. The website wikipositive.org provides the name of a firm, a description of the firm's business and the country of incorporation, then, we hand-match the 119 firms within the Thomson Reuters Datastream dataset using all the information available on each firm's website to further ensure the accuracy of the data reported by wikipositive.org. With respect to the geography distribution, 54.6% (65) of firms are incorporated in the USA and Canada, 26% (31) are incorporated in Europe, 13.5% (16) in Asia, 3 firms in Africa, 2 firms in South America and in Australia. With respect to the social investment areas, Table 1 shows the high presence of firms in the environmental and energy sector (56.3%) and in the health sector (17.7%).

6. Empirical results

In this section we present the results of our empirical analysis.

We have taken three scenarios for α in formula (1), i.e. $\alpha = 0.1, 0.5, 0.9$. The case $\alpha = 0.1$ describes the situation that penalizes – in terms of connections

Table 2: Solutions of Problems $\mathcal{P}_H$ and $\mathcal{P}_E$ when setting $K^\star = 2$. The cases of $\alpha = 0.1, 0.5, 0.9$ are distinguished.

	Entropy			Euclidean distance		
	$\alpha = 0.1$	$\alpha = 0.5$	$\alpha = 0.9$	$\alpha = 0.1$	$\alpha = 0.5$	$\alpha = 0.9$
Minimum value	0.0149	0.0019	0.0002	5.3024E-07	5.2592E-08	3.0487E-08
$j^\star$	6	6	3	46	46	3

between pairs of firms – the social impact compliance similarity in favor of the values of the SIF compliance score. The scenario with $\alpha = 0.9$ works in the opposite direction, giving less credit to the value of the social impact compliance measures and more to the distance between firms. The case $\alpha = 0.5$ is the fair balanced situation.

The selected functions in (1) are

$$f(|\mu_i - \mu_j|) = -|\mu_i - \mu_j|^2 + 1; \qquad g(\mu_i, \mu_j) = \frac{\mu_i + \mu_j}{2}.$$

Here we consider only the contiguous partitions with two elements, so that we fix $K^\star = 2$ in Problems $\mathcal{P}_H$ and $\mathcal{P}_E$ and remove for now K from the set of the control variables of the considered optimization problems. The selection of $K^\star = 2$ meets a reasonable target of the optimal partition problem. Indeed, in doing so we separate the case of firms with high level of SIF compliance score that are connected to firms with high level of SIF compliance score - i.e. high value of the clustering coefficients - from the opposite case of low clustering coefficient, in which such a virtuous pattern does not take place. In this way, the optimal partition $\pi^\star(2) = \{\pi_1^\star, \pi_2^\star\}$ is identified by one label $j^\star = 1, \dots, 119$ such that $\pi_1^\star = \{c_1, \dots, c_{j^\star}\}$ and $\pi_2^\star = \{c_{j^\star+1}, \dots, c_{119}\}$.

Table 2 collects the results of the optimization procedure.

Our results highlight that the distribution of the original collection of clustering coefficients is quite similar to the one of the optimal partition when similarity is measured through the Euclidean distance and – in both cases of Entropy and Euclidean distance – when the strength of the connections between the nodes of the network is mainly due to their distance in terms of the SIF compliance score. Such outcomes have an intuitive interpretation. Indeed, the analyzed firms can be effectively clustered in two groups with respect to their community structures. The obtained clusters are more similar to the original sample in terms of the average similarity of the individual firms rather than for the shapes of their overall distributions – even if it is important to point out that also the values of the entropies are low. Substantially, the clusters of firms reproduce the original sample more in terms of position parameters rather than in terms of empirical distribution.

For the cases of $\alpha = 0.5$ and $\alpha = 0.1$, the entropy approach offers results more focused on the number of companies than on their particular identification. Specifically, the cluster of weak community structures is formed by six firms from a set of 58 firms in both cases. This outcome is in line with the criterion adopted by the entropy in the context of clustering, i.e. with its attitude of lumping together firms on the basis of the shape of the distributions of their clustering coefficients disregarding their individual values. Under a financial perspective, the obtained findings are rather inconclusive, in that it prevents from a detailed description of the main features of the obtained clusters.

The case $\alpha = 0.9$ is the one where one gives more credit to the distance between firms, hence leading to a diluted entropy-based effects on the shape of the distribution. This explains why we obtain results at a more individual firm level for $\alpha = 0.9$.

In addition, the preference for high values of α suggests that firms can be more effectively clustered when connections are established under the perspective of the SIF compliance score, while clusters are identified less appropriately when strong links mean that a given pair of firms has highly virtuous behavior in pursuing social impact targets.

When looking at the optimal cutting point $j^\star$, we notice that entropy is minimized when a few firms with weak community structures are separated from the others, this points out the presence of outliers at low clustering coefficients level. More specifically, three firms are separated from the others, showing the maximum level of the SIF compliance score. This result is also true for the

Euclidean distance case when $\alpha = 0.9$, which is a further confirmation of such a peculiar behavior of the firms with strong SIF compliance score distance-based communities. This finding reflects two key aspects of the SIFs: the cohesion of the social impact compliance pattern and the tendency to pertain to the middle/low level of the SIF compliance score.

When the connections of the firms are not mainly due to the distance of the SIF compliance score – i.e. for $\alpha = 0.1$ and $\alpha = 0.5$ – then we have a clustering of the firms in two quite balanced groups of low (46 firms) and high (73 firms) community structures. Such a clustering does not reproduce the original sample in terms of empirical distribution similarity, but rather in terms of the average of the distances between the clustering coefficients values at individual firm level. If we look at the SIF compliance score between the two clusters, we observe that the 46 firms have the lowest value of the score, while the 73 firms are concentrated in the middle-high level of the score.

Interestingly, these two groups of firms emerge as a handy analysis tool for a deep exploration of the features of the firms even when the SIF compliance score seems alike. The analysis of the distribution of the firms across economic sectors (i.e. social target areas) and countries targets the discovery of SIF compliance patterns (if any) within each cluster. We start out by considering for each firm in our sample the economic sector and the country as both variables are widely considered in the ESG/CSR literature (see for instance, Auer and Schumacher, 2016; Ortas et al., 2015 and Jitmaneeroj, 2016) and likely to be relevant also for SIIs. This analysis offers valuable insights. First, the results could highlight possible common paths among firms at high/low level of the SIF compliance score. Second, the presence (or the lack) of common paths in the economic sectors and countries among firms that share a similar level of SIF compliance score could shed some light on the possibility to identify prospective SIFs on the basis of available information on sector and country. This examination is reported in Tables 3, 4 and 5.

Contingency Tables 3 and 4 examine the distribution of economic sectors and countries between the two clusters, respectively. Observing the economic

Table 3: Description of the clusters on the basis of the economic sectors. The table shows the number and the percentage of firms within each cluster by economic sector. The value of the Pearson $\chi^2(7)$ is 8.369, with p-value 0.301, while Fisher's exact has p-value 0.362.

Cluster	**Agriculture**	**Education and Training**	**Environment and Energy**	**Financial Services**	**Health**	**ICT**	**Water and Sanification**	**Housing**	**Total**
Cluster 1	5 (55.6%)	2 (100%)	41 (61.2%)	3 (75.0%)	9 (42.9%)	4 (66.7%)	7 (87.5%)	2 (100%)	73 (61.3%)
Cluster 2	4 (44.4%)	0 (0.00%)	26 (38.8%)	1 (25.0%)	12 (57.1%)	2 (33.3%)	1 (12.5%)	0 (0.00%)	46 (38.7%)
Total	9	2	67	4	21	6	8	2	119

Table 4: Description of the clusters in terms of regional realities. The table shows the number and the percentage of firms within each cluster by country. The value of the Pearson $\chi^2(5)$ is 3.0198, with p-value 0.697, while Fisher's exact has p-value equals to 0.650.

Cluster	**Africa**	**Asia**	**Australia**	**Europe**	**South America**	**United States**	**Total**
Cluster 1	2 (66.7%)	12 (75.0%)	1 (50%)	21 (67.7%)	1 (50%)	36 (55.4%)	73 (61.3%)
Cluster 2	1 (33.3%)	4 (25.0%)	1 (50%)	10 (32.3%)	1 (50%)	29 (44.6%)	46 (38.7%)
Total	3	16	2	31	2	65	119

Table 5: Description of the clusters: firm size and profitability. The table provides mean values of social impact firms' total assets and ROA from 2015 to 2019.

	Cluster 1		**Cluster 2**		
	N	Mean	N	Mean	t-stat
Total Assets 2015	54	7,373.51	29	16,775.67	-1.503
Total Assets 2016	54	8,323.97	28	18,362.84	-1.471
Total Assets 2017	52	9,114.36	26	21,068.06	-1.565
Total Assets 2018	49	8,209.26	23	23,858.17	-1.820
Total Assets 2019	46	9,183.72	21	26,121.40	-1.879
ROA 2015	52	0.08	26	-0.14	1.081
ROA 2016	53	0.07	27	-0.51	0.989
ROA 2017	50	0.11	25	-0.59	1.055
ROA 2018	49	0.08	22	-0.62	0.971
ROA 2019	45	0.07	21	0.00	0.081

sectors, we find that the health sector, differently from the other sectors, shows a prevalence of firms in Cluster 2, that is in the cluster of firms with the relatively low value of the score. However, the chi-squared test shows that there is no statistically significant difference in the distribution of sectors and countries between firms in Cluster 1 and Cluster 2. These initial finding suggests that sector and country of origin do not act as a differentiator in the level of compliance that each firm shows in terms of SIF identification criteria. Put it differently, the investigated firms approach the issue related to the compliance to SIF requirements regardless of the sector or the country.

We then move to the analysis of two main firm characteristics, size and profitability, and their relative distribution in the two clusters. In Table 5 we report t-test statistics on the null hypothesis of equal mean in the size (as proxied by Total Asset, expressed in thousands USD) and profitability (as proxied by Return on Assets, defined as EBITDA over Total Assets) of firms in the two observed clusters for each year. Results show that firms that belong to Cluster 1, that is firms with a higher level of SIF compliance score, tend to be smaller and more profitable (with a positive average ROA, versus a negative average ROA of firms of Cluster 2). However, there is not statistically significant evidence in terms of profitability, while we observe a statistically significant difference in terms of size in the most recent years (2018-2019). This finding suggests that firms more compliant with the social impact definition tend to be smaller, but at the same time as profitable as firms that engage in less impact-oriented type of business.

7. Conclusions

In this paper, we detect communities of SIFs, which represent one and less investigated destination of the SII. As the market for SII is growing rapidly and is attracting interest from mainstream investors, accurate and specific SIF evaluations are increasingly requested by managers, investors and public-decision makers in order to identify the boundaries for this particular asset class, as well as to classify potential targets on the basis of their relative degree of compliance with the minimum required features.

For this purpose, we construct the SIF compliance score of a sample of listed firms across many countries and map it through a complex network approach. Firms are viewed as nodes of a weighted network, whose connections depend on the degree of compliance of each firm to SIF criteria provided by OECD (2015). Specifically, highly connected firms are those similar in terms of their social impact compliance measure and, at the same time, with high value of such a score.

The network analysis outlines the main characteristics of the formed clusters. When clusters are detected on the basis of the degree of similarity among the SIF compliance score, we observe the inclusion of almost all firms in one cluster, while only a few ones are included in the second cluster showing the highest level of the SIF compliance score. The relatively low number of outliers demonstrates that very few firms are fully compliant with the OECD minimum requirements.

Conversely, when the connections of the firms are analyzed on the basis of the level of the SIF compliance score, we have a clustering of the firms in two quite balanced groups of high community structures at a low SIF compliance score level (46 firms) and low community structures at a high SIF compliance score level (73 firms).

We find some evidence that the size of firms varies between firms with a high/low level of the SIF compliance score. Indeed, firms which are more compliant with the SIF requirements tend to be smaller, especially in the past few years. Moreover, our results reveal that (i) the compliance to SIF requirements transcends the sectorial and national barriers, so that firms do not necessarily apply SIF models tailored to their industry or country, and (ii) the profitability of a firm does not vary with the SIF compliance score.

Our findings are particularly interesting for investors, asset managers and firm governance because of their relevant implications in terms of portfolio selection and - ceteris paribus - in the firm's commitment towards social impact. Indeed, the former results suggest that investors should consider the SIF compliance of the targeted firm and not the corresponding pattern at the industry or country level. This is consistent with previous findings in the related field of ESG factors (see, for instance, Iamandi et al., 2019), which state that any sustainability identification strategy should match the individual case of each and every business organization.

Instead, the latter results seem to suggest the absence of a trade-off between a high level of impact and profitability, and are consistent with the GIIN 2017 Report Conclusion (GIIN, 2017). In addition, this is again in line with some findings in the ESG field (see, for instance, Friede et al., 2015; DWS Fund, 2015; Morgan Stanley, 2019).

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