World Scientific
www.worldscientific.com

DO FIELD PARTNERS ADD VALUE TO CROWDFUNDED MICROFINANCE? AN INDUSTRY APPROACH

ROBERTO MORO-VISCONTI*

*Dipartimento di Scienze dell'Economia e della Gestione Aziendale
Università Cattolica del Sacro Cuore, 20123 Milan, Italy
roberto.moro@unicatt.it*

SALVADOR CRUZ RAMBAUD

*Departamento de Economía y Empresa
Universidad de Almería, 04120 Almería, Spain
scruz@ual.es*

JOAQUÍN LÓPEZ PASCUAL

*Departamento de Economía de la Empresa
Universidad "Rey Juan Carlos", 28032 Madrid, Spain
joaquin.lopez@urjc.es*

The *framework* of this study is the field of crowdfunded microfinance that represents a way to scale up financial access, leveraging digital technology applications. A key element of this value chain is the field partner, represented by a local Microfinance Institution (MFI) that intermediates between the crowdfunding platform and the individual borrowers or group of borrowers. In this context, the *main objective* of this paper is to measure the financial and prosocial contributions of field partners through crowdfunded microloans. *Methodologically*, this prosocial impact is measured with an innovative approach, by using network theory to describe the supply and value chains that link crowdfunding investors to field partners and, consequently, to micro-borrowers. The *main contribution* of this study is the introduction of a global indicator able to quantify the increase of the social impact and the financial system of a country, coming from the presence of ESG-compliant crowdfunded microloans.

Keywords: Microlending; digital networks; sustainable development goals; ESG; group lending; Kiva.

JEL Classifications: G21, G51, O35

*Corresponding author.

1. Introduction

Microfinance Institutions (hereinafter, MFIs) play the role of lenders for unbanked/underbanked individuals or groups, getting back lent capital plus an interest rate for their intermediatory risk-taking activity. This allows lots of modest collectives to access entrepreneurship, with a bottom–up impact that fosters the well-known Sustainable Development Goals (SDGs). The increasing awareness of sustainability, especially among young people, led the United Nations member states to promote, in 2015, the SDGs which mainly aim for the prosperity of developing and undeveloped world countries.

More generally, people are sensible about achieving these goals which materialize their hopes for a sustainable future. In this context, microloans reinforce their prosocial character fundamentally due to three reasons: (a) the volume of money allocated towards microloans is higher; (b) the main aim of the new borrowers is sustainability; and (c) the emergence of nonprofit digital platforms that offer interest rate-free capital, collected through these crowdfunding sources.

Crowdfunded microfinance enables MFIs to share the risk of a microloan among a set of individuals in wealthy countries who provide funding for the loans made by MFIs in poorer countries (Anglin *et al.* 2020).

Undoubtedly, crowdfunding has given people the opportunity of becoming microlenders, then satisfying their need to contribute to a more sustainable world. However, crowd-funders must support possible losses due to delinquency or default of micro-borrowers and this could dissuade potential lenders from investing their money in crowdfunded microloans.

These criticalities may be softened by the inclusion of field partners that "securitize" their microloans through the so-called crowdfunding platform. Now, the risk is supported by the field partner but may be minimized by careful selection of borrowers and controversial high interest rates applied to compensate for potential insolvency.

Moreover, field partners reduce information asymmetries, and repayment delinquency, justifying their intermediation. Crowd-funders complement this value-adding chain, by providing interest rate-free finance, and reducing the MFI capital rationing concerns, eventually promoting both sustainability and outreach to the unbanked.

Within this broad context, the main objective of this study is to quantify the social impact and the value added by crowd-funders to the financial system when they are incorporated into the structure of an MFI. This value will be composed by the aggregation of two indicators: (a) the closeness of an MFI to the achievement of SDGs; and (b) the improved solvency (and the specular decrease in default risk) of MFIs when new borrowers are included in a funding project. These indicators attract crowdfunding sponsors, as they foster socio-economic sustainability.

From a methodological point of view, the first indicator will be defined as the Pearson correlation coefficient arising from the regression between the resources assigned to the different sectors of the economy by the MFI and the number of SDGs
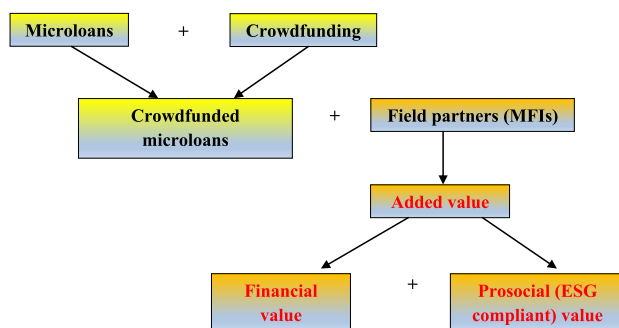
Fig. 1. Schematic of the target of this study.

related to such economic sectors. This indicator has the important advantage that it varies from -1 to $+1$. On the other hand, the second indicator will be defined as the increase of entropy before and after the inclusion of new micro-borrowers.

The main contribution of this study is the introduction of a global indicator able to measure the financial and prosocial values added by field partners to the economic system of a country through the so-called crowdfunded microloans. The target of this paper can be visualized in Fig. 1.

This study is structured as follows: After this introduction, Section 2 illustrates the consistency between crowdfunded microloans and the SDGs. Section 3 is dedicated to a short revision of the extant literature. Section 4 describes the methodology of the study, and Sec. 5 presents the results. Section 6 contains a critical discussion, before the conclusions summarized in Sec. 7.

2. Crowdfunded Microloans and the Sustainable Development Goals

Sustainability is based on three main dimensions: economic, social, and environmental (Alsayegh *et al.* 2020). This established taxonomy is consistent with the Environmental, Social, and Governance (ESG) indicators, with the SDGs, and with a more institutional framework, represented by Political, Economic, Social, Technological, Legal, and Environmental (PESTLE) considerations. The interactions among these three systems are shown in Fig. 2.

ESG parameters represent a complementary representation of the SDGs: Whereas the latter are somewhat wider, the former are increasingly measured by the assessment of ESG-compliant listed firms (Antoncic *et al.* 2020), providing growing benchmarking evidence even for unlisted securities. In this way, ESG evidence from listed MFIs represents a further research stream that may provide a benchmark for less-structured field-partnering MFIs. ESG compliance represents a prerequisite for socially responsible investments.

On a corresponding side, PESTLE analysis represents an institutional framework of macro-environmental factors used in the environmental scanning component of strategic management.

Fig. 2. Interactions among SDGs, PESTLE, and ESG parameters.

Table 1 [adapted from Moro Visconti (2021)] summarizes the correspondence between the 17 Sustainable Development Goals and the characteristics of crowd-funded microfinance.

3. Securitizing Microloans: The Role of Field Partners in the Literature and the Case of Kiva

Financial institutions and funding mechanisms are rapidly evolving. Entrepreneurs are combining equity start-up finance (e.g. family and friends, angel investors, venture capitalists, and private equity funds) and then (when they can afford it) traditional bank debt, with microfinance (Khavul 2010), crowdfunding (Belleflamme *et al.* 2013), peer-to-peer (P2P) lending, and other financial innovation instruments (Moenninghoff & Wieandt 2012). Consequently, microfinance, crowdfunding, and peer-to-peer lending provide some excellent examples of new financial alternatives that play a significant role in the design of new financial products for entrepreneurship in both developed and developing countries.

After the boom of microfinance, we witness a boost in crowdfunding. It is so interesting to study their interactions (Attuel-Mendes 2016). Crowdfunding and peer-to-peer lending are two of the many FinTech applications [for a taxonomy, see Moro Visconti *et al.* (2020)] that can evolve incorporating artificial intelligence and machine learning patterns (Allen *et al.* 2021). In the last decade, the introduction of smartphones combined with key developments in cryptography (blockchains) and artificial intelligence has revolutionized the workings of every finance function — from payments to credit, and from equity financing to asset management.

As crowdfunding is rapidly spreading across developing economies, it is emerging as a way of allowing individual investors to pool small amounts of money to meet the funding requirements of new and expanding ventures. As a financial innovation,

crowdfunding has diffused from an initial launch in several developed economies and is rapidly spreading across developing economies (Kukk & Laidroo 2020).

Kiva, the largest crowdfunding intermediary, is probably the best exponent of using social media to raise financing. Kiva aggregates the funds from individuals and places them as blocks with microfinance organizations, which are then responsible for the disbursement and management of the loans to entrepreneurs (Kiva 2020).

In essence, Kiva acts as an online bridging platform between borrowers and lenders. The profiles of people from developing countries who are in search of microcredit are posted on Kiva's platform. Lenders browse the different profiles and invest money in their preferred projects, according to the characteristics of the loan request and the borrower. On the other hand, borrowers pay interest to the intermediaries of the financing process, referred to as field partners (the MFIs), who are essentially the ones that bear most of the risk. The sponsored MFI pays back Kiva the capital, with no interest charges, softening its cost of collected debt (typically in hard currency, such as the USD).

Every Kiva loan is offered by a local partner to a micro-borrower and the MFI partner works with Kiva to get funding for that loan from lenders. The association between a crowdfunded loan and an on-field partner is of great importance since the loan risk is closely correlated to the reputation of the partner. This is why Kiva tries to assign a risk rating to every partner, when possible, following an annual due diligence process.

To mitigate the risk, each borrower is screened by a local Kiva field partner before their application is posted on the Kiva website. This field partner plays a role as a rating agent to look at a variety of factors (such as loan history, village or group reputation, and loan purpose) before deeming a borrower to be creditworthy. Despite these precautions, a variety of factors can result in borrowers defaulting. Digitalization of credit history and big data gathering and processing, even using cloud storage, validating blockchains, and artificial intelligence interpretation, add value to the intermediation chain.

Borrowers who are more intensely monitored by MFIs are more likely to repay crowdfunded loans on time. Monitoring is particularly important in reducing repayment problems of individual loans rather than group-based loans. In this way, crowd-funders are interested in knowing the ability of MFIs to monitor loans through a measure of their prosocial and financial impacts (Berns *et al.* 2021).

By the end of the month, Kiva generates a bill to charge the field partner for all the collected repayments. Kiva works on a net billing system. Kiva subtracts the number of repayments that a field partner owes to Kiva lenders from the amount that a field partner fundraises for entrepreneurs on Kiva. If the balance is positive, this means that the partner has raised more than they need to repay, and Kiva uses those funds to credit the lender account with the repayments due to them. If the balance is negative, then the partner has to send a payment to Kiva for the balance. As soon as Kiva receives that payment, the organization uses those funds to credit

Table 1. Comparison among SDGs and crowdfunded microfinance.

Sustainable Development Goal	Crowdfunded microfinance
(1) No Poverty	Microfinance, lending to the bottom of the pyramid unbanked, can contribute to reducing poverty, providing financial access to the unbanked.
(2) Zero Hunger	Microfinance can be linked to healthcare improvements, even if these investments do not generate an immediate payoff. Hunger can be reduced with pro-growth micro-projects.
(3) Good Health and Well-being	Poverty and hunger reduction improves health and well-being.
(4) Quality Education	Education is not a direct object of microloans since it does not produce immediate refundable liquidity but can be improved by microfinance-driven higher living standards. Education is a key pillar of development, representing a long-term investment that can be partially funded with microloans.
(5) Gender Equality	Microfinance, lending mostly to women (Aggarwal *et al.* 2015), promotes gender equality. Microfinance has a strong gender-effective impact. Field partners who are noted for higher social performance because they focus on lending to women, are more likely to see their loans refinanced (Dorfleitner *et al.* 2021).
(6) Clean Water and Sanitation	No direct impact, but a positive trickle-down effect, on medium-sized big projects. Small projects funded by MFIs can improve access to clean water.
(7) Affordable and Clean Energy	Small projects (micro-wind, micro-solar) funded by microloans can improve access to solar panels. Bigger infrastructural projects are out of the scope for MFIs.
(8) Decent Work and Economic Growth	Small jobs can be upstarted by microloans, igniting economic growth.
(9) Industry, Innovation, and Infrastructure	Small-size innovation is a target of microloans that are, however, out of the scope if we consider infrastructural investments.
(10) Reducing Inequality	Microloans to unbanked poor reduce inequality. See SDG (5).
(11) Sustainable Cities and Communities	The socio-economic impact of microloans positively affects sustainability.
(12) Responsible Consumption and Production	This is not an immediate target of microfinance, even if ESG-compliant lending may be linked to responsible consumption and production.
(13) Climate Action	Climate is a macro-issue, beyond the scope of most MFIs, even if micro-intervention can strengthen bottom–up contribution to the cause.
(14) Life below Water	Little if any direct implication. Extensive fishing, if fueled with micro-credit, exacerbates the problem.
(15) Life on Land	Little if any direct implication. Environmental issues are not a prioritizing target of microfinance, but they can be linked to ESG-compliant schemes.
(16) Peace, Justice, and Strong Institutions	The reduction of financial exclusion has a positive impact on peacekeeping.
(17) Partnerships for the Goals	MFIs improve their efficacy by working together with other players, from group lenders to crowd-funders or other financial intermediaries. Crowdfunding platforms, MFIs, and other stakeholders synergistically partner for the goals.

the lender account with the repayments due. Once the repayment is made to the lender, the lender may choose to re-lend the funds, donate them to Kiva's operating expenses, purchase a gift certificate, or withdraw them to be credited to the lender's PayPal account (Moleskis & Canela 2016).

A default occurs when a borrower or a field partner fails to make payments on a loan to the field partner or Kiva, respectively. Kiva field partners screen loan applications before accepting them.

Berns *et al.* (2020) show that crowd-investors use Kiva as a delegated monitoring platform in crowdfunded microfinance. The repayments are collected by the field partner and the funds are then funneled back to Kiva lenders. Every step of this digital process is completed online through the Kiva platform. This concept of lending with no expected financial gain, while bearing a default risk, is a distinguishing feature of a handful of online crowdfunding platforms, most notably Kiva.

Uddin *et al.* (2018) consider the Kiva microcredit system, which provides a characterization (rating) of the risk associated with the field partner supporting the loan, but not of the specific borrower who would benefit from it. After joining Kiva, MFIs' sustainability improves and interest rates decrease (Luo *et al.* 2022).

4. Methodology

Figure 3 describes the value and supply chain that link investors through the crowdfunding platform to the field partners and eventually to micro-borrowers. This is consistent with the social networking "homophily" described by Burch *et al.* (2014) that eventually links crowdfunding investors to micro-borrowers through the crowdfunding platform and then the MFI.

This methodology is also consistent with the research question that investigates the value added by field partners through crowdfunded microloans. When analyzing this value, two approaches could be considered:

(1) The field partner plays the role of a traditional bank in a syndicated loan, but with the noteworthy differences shown in Table 2.
(2) The field partner is an MFI that "securitizes" its microloans, making it possible for potential lenders (or lending groups) to participate in social and sustainable businesses.

This intermediating role of field partners implies important advantages:

(i) The principal amount of microloans is granted by the crowd-lenders and so the field partner need not put (eventually advance) any money.
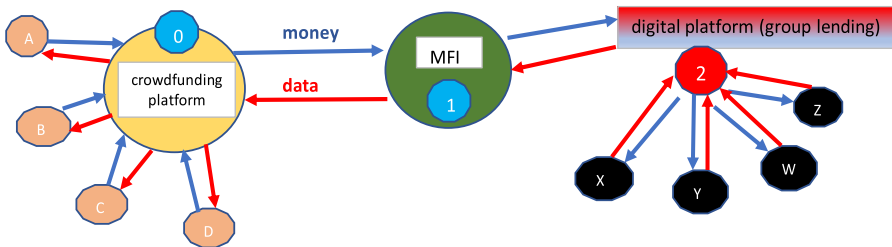

Fig. 3. Bridging edges $(0 \leftrightarrow 1 \leftrightarrow 2)$ between crowdfunding and microfinance.

Table 2. Differences between syndicated loans and crowdfunded microloans.

Variable	Syndicated loan	Crowdfunded microloan
Involved amount	Very high	Very low
Number of borrowers	One	Several
Number of lenders	Few	Many
Gain	Money interest	Money and social interest

(ii) In most cases, the (high) interest is only received by the field partner because the lenders only receive the loan principal.

(iii) The risk is supported by the field partner but may be minimized by a careful selection of borrowers and the high interest rates applied to compensate for potential insolvency. Despite the reduction of risk, the interest rates continue to be relatively high.

Therefore, the value added by a field partner can be decomposed into the following items:

(i) An important increase in the numbers of borrowers and lenders involved in the operation (outreach maximization).

(ii) The substitution of the purely banking interest by a mix of financial interest (cashed by the field partner) and "social" interest (morally attributable to crowd-lenders).

Consistently with these premises, this study will measure:

(1) the prosocial impact of field partners by scoring its relationship with the SDGs;

(2) the purely financial impact of field partners, differentiating between individual lending and group lending.

Task #1 will be developed in Sec. 5.1 by using the Pearson correlation coefficient derived from the regression between the number of microloans per economic sector and the weight of an industry within the SDGs. Task #2 will be described in Sec. 5.2 and will be performed with an innovative network theory application.

5. Results

5.1. *Measuring the prosocial impact of field partners*

The positive effect in an economy of the increase of funded businesses is obvious, as it promotes financial inclusion. However, the influence of the "social" figurative interests in an economic system is difficult to measure independently of the fact that the field partner is an MFI, a social business, a school, or a nonprofit organization. A possible methodology to quantify these "social" interests is to estimate the proximity of the field partner's investments to the fulfillment of the so-called SDGs. This last aspect of field partners' role is reinforced by Internet crowdfunding platforms that catalyze the "social economy".

Table 3. The numbers of microloans in different sectors.

Sector of activity	No. of microloans	Percentage	Related SDGs	Score
Agriculture	103	26.75%	(2), (6), (13), (14), (15), (17)	6
Retail	82	21.30%	(12), (13), (17)	3
Food	76	19.74%	(3), (6), (8), (9), (12), (17)	6
Clothing	30	7.79%	(3), (6), (8), (9), (12), (17)	6
Services	28	7.27%	(17)	1
Housing	24	6.23%	(11), (17)	2
Education	12	3.12%	(1), (4), (5), (10), (17)	5
Transportation	9	2.34%	(3), (9), (11), (13), (17)	5
Personal use	8	2.08%	(17)	1
Arts	5	1.30%	(11), (15), (17)	3
Construction	3	0.78%	(9), (11), (13), (15), (17)	5
Health	3	0.78%	(1), (2), (3), (17)	4
Manufacturing	1	0.26%	(3), (6), (8), (9), (12), (17)	6
Wholesale	1	0.26%	(12), (13), (17)	3
TOTAL	385	100.00%	—	—

Table 3 sets a correspondence between the sectors financed by crowdfunded microloans, in a sample of 385 microloans granted by Kiva, with the 17 SDGs.

Kiva has been selected as it represents one of the most important MFIs in the United States microcredit market. In effect, the three main MFIs in the United States are the Pacific Community Ventures (founded in 1998 to provide microloans in California), CDC Small Business Finance Corp. (founded in 1978, and operates in Arizona, California, and Nevada), and Kiva (founded in 2005, is headquartered in San Francisco). Additionally, Kiva represents the most visited microfinance website (with over 10 million visits per year — https://www.similarweb.com/it/website/ kiva.org/#traffic) and is a celebrated nonprofit crowdfunding platform. The data have been obtained from the website: https://www.kiva.org/build/data-snapshots, whence the information about the loans granted by Kiva was freely downloaded. Following sampling techniques, we have selected 385 loans granted in the period from 2008 to 2020 as shown in Table 3.

This way, we will be able to quantify the prosocial gains provided by crowdfunded microloans to the added value of an economy.

In Table 3, we have assigned a score to each sector, according to the number of related SDGs. This will allow correlating the percentage of amount (or the number of borrowers) with this novel SDG index, and effectively check if there is a positive and prosocial assignment of financial resources to those businesses identified with the SDGs, then leading to efficiency. The degree of association is given as usual by the Pearson correlation coefficient (between -1 and $+1$).

The geographical distribution is reported in Table 4.

The results of the regression show that there is no resource assignment according to the association between sectors of the economy and related SDGs. In effect, the Pearson correlation coefficient is very low ($r = 0.010610283$) and the coefficient derived from the regression is not significant at 95% level ($p > 0.05$).

Table 4. Numbers of microloans of the sample by countries.

Country	Number of microloans
Afghanistan	1
Albania	1
Armenia	1
Azerbaijan	4
Benin	1
Bolivia	7
Burkina Faso	1
Cambodia	15
Chile	1
Colombia	8
Congo	1
Costa Rica	1
Dominican Republic	1
Ecuador	8
El Salvador	13
Fiji	1
Georgia	2
Ghana	2
Guatemala	1
Haiti	4
Honduras	6
India	1
Indonesia	3
Jordan	2
Kenya	40
Kyrgyzstan	3
Lebanon	2
Liberia	4
Madagascar	2
Malawi	1
Mali	1
Mexico	5
Mongolia	1
Mozambique	2
Nepal	1
Nicaragua	6
Nigeria	6
Pakistan	13
Palestine	2
Paraguay	9
Peru	22
The Philippines	91
Rwanda	7
Samoa	7
Senegal	4
Sierra Leone	6
Tajikistan	21
Tanzania	4
Togo	6
Tonga	2

Table 4. (*Continued*)

Country	Number of microloans
Turkey	2
Uganda	14
Ukraine	1
The United States	1
Vietnam	12
Zambia	1
Total	385

The Global Commission on Business and Sustainable Development asked Corporate Citizenship to elaborate an analysis of the SDGs by sectors to identify business opportunities and risks (2016). In this report, 10 industry sectors were identified: oil and gas, basic materials, industrials, consumer goods, healthcare, consumer services, technology, telecommunications, utilities, and financials. These 10 industry sectors were mapped across the primary, secondary, and tertiary sectors of the economy, and classified according to the following criteria:

- sectors with strong linkages to a single SDG;
- sectors with linkages to two or more SDGs;
- sectors that act as an enabler across all SDGs.

The results are summarized in Table 5.

Unfortunately, this linkage cannot be used for the data obtained from the Kiva website because this nonprofit organization uses another classification of industry sectors, different from that of Table 5. This is the reason why we have used Table 3 instead.

A sector should not be classified as "good" or "bad" depending on the score which measures its proximity to the 17 SDGs. In effect, by assuming the same relative importance to all SDGs, this index simply aims to represent the degree of fulfillment of the aforementioned objectives when a sector is supported through financing. So, this means that a specific sector will help to satisfy more SDGs than another one.

Table 5. Linkage of SDGs to the industry sectors.

Industry sector	Linked SDGs
Oil and gas	(7)
Basic materials	(12), (15)
Industrials	(2), (12), (14)
Consumer goods	(2), (12), (14)
Healthcare	(3)
Consumer services	(2), (12), (14)
Technology	All
Telecommunications	All
Utilities	(6), (7), (9)
Financials	All

It is possible that, in African countries, the scores assigned to Agriculture (6) and Housing (2) reflect the true preferences of the population as in these countries there is a problem of famine but, taking into account their lifestyle, there is not a problem of housing. However, this could not be the case in Asian countries where the scarcity of houses is an important problem. Then, a possible solution could be to assign a different score to each SDG depending on the specific country and even the time of the analysis. Nevertheless, our aim in this paper has been to propose a general index of closeness.

Considering that all real assignments of loans to industry sectors add value to the prosocial impacts of MFI loans, we are going to present the following approach. Assume that n_k loans have been assigned to the kth SDG with a score p_k. Thus, the total score of this assignment is $\sum_{i=1}^{n} n_k p_k$. Assume now that n_k and p_k are increasingly ordered giving rise to n'_k and p'_k, respectively. Obviously, $\sum_{i=1}^{n} n_k p_k \leq \sum_{i=1}^{n} n'_k p'_k$, which allows us to construct the ratio r, and then the factor $1 + r$ is always greater than 1. Thus, any assignment creates prosocial value for the economy.

5.2. *Measuring the purely financial impact of field partners*

5.2.1. *Preliminary concepts*

In the analysis conducted in the following paragraphs, each link between any two nodes within a network vehiculates either data, money, or both.

- An *adjacency matrix* is a square matrix whose elements indicate whether any pair of vertices (nodes) are adjacent or not in each network.
- A *simple network* is an undirected graph (with all linking edges being bidirectional) where neither loops (edges from a vertex to itself) nor multiple edges are allowed. In a simple network N, the adjacency matrix A is a square matrix whose elements a_{ij} are 1 (if there is an edge from vertex i to vertex j) or 0 (if there is no edge from i to j). As a consequence, the adjacency matrix of a single network is symmetric and the diagonal is exclusively composed of zeros.
- An interesting *property* of adjacency matrices is the following: If A is the adjacency matrix of an undirected network, then the (i, j)th element of the power matrix A^n gives the number of undirected walks of length n from i to j.

In the next analysis, we will distinguish between traditional and crowdfunded microloans.

5.2.1.1. Traditional microloans

Traditional microloans (e.g. in the absence of crowdfunding) are represented by individual or group lending. They can be described with network theory, in graphical form, or using adjacency matrices. They are divided into two main categories [individual loans (A) and group lending (B)] and incorporate the risk of default (C).
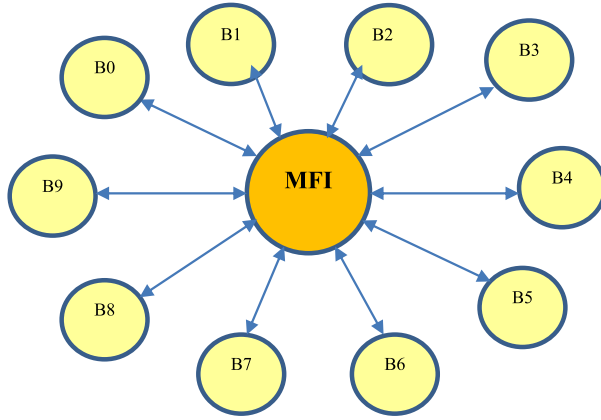
Fig. 4. Individual lending with 10 micro-borrowers.

(A) Case of an individual lending

In a traditional model, the MFI is related to its n micro-borrowers, according to a simplified radial scheme. Figure 4 is an example of individual lending from the MFI to micro-borrowers who are not connected among them. Specifically, it shows an MFI working with 10 micro-borrowers (from B_0 to B_9). This network is easy to monitor by the MFI which acts as a pivoting (central) node, collecting information and intermediating loans.

In this case, by considering that the relationship between each micro-borrower and the MFI is bilateral, the adjacency matrix is reported in Table 6. The adjacency matrix of this undirected (bidirectional) network provides a mathematical description of the links, showing how the network works and how the degrees of each node can be measured.

Tables 6 and 7 represent a sample of how each node's degree can be calculated, mapping the network and providing a basic measure of its properties. Adjacency

Table 6. Adjacency matrix corresponding to Fig. 4.

Nodes	MFI	B_0	B_1	B_2	B_3	B_4	B_5	B_6	B_7	B_8	B_9
MFI	0	1	1	1	1	1	1	1	1	1	1
B_0	1	0	0	0	0	0	0	0	0	0	0
B_1	1	0	0	0	0	0	0	0	0	0	0
B_2	1	0	0	0	0	0	0	0	0	0	0
B_3	1	0	0	0	0	0	0	0	0	0	0
B_4	1	0	0	0	0	0	0	0	0	0	0
B_5	1	0	0	0	0	0	0	0	0	0	0
B_6	1	0	0	0	0	0	0	0	0	0	0
B_7	1	0	0	0	0	0	0	0	0	0	0
B_8	1	0	0	0	0	0	0	0	0	0	0
B_9	1	0	0	0	0	0	0	0	0	0	0

Table 7. Adjacency matrix corresponding to Fig. 5.

Nodes	MFI	B_0	B_1	B_2	B_3	B_4	B_5	B_6	B_7	B_8	B_9
MFI	0	1	1	1	1	1	1	1	1	1	1
B_0	1	0	1	1	1	1	1	1	1	1	1
B_1	1	1	0	1	1	1	1	1	1	1	1
B_2	1	1	1	0	1	1	1	1	1	1	1
B_3	1	1	1	1	0	1	1	1	1	1	1
B_4	1	1	1	1	1	0	1	1	1	1	1
B_5	1	1	1	1	1	1	0	1	1	1	1
B_6	1	1	1	1	1	1	1	0	1	1	1
B_7	1	1	1	1	1	1	1	1	0	1	1
B_8	1	1	1	1	1	1	1	1	1	0	1
B_9	1	1	1	1	1	1	1	1	1	1	0

matrices also represent a starting point for the interpretation of multilayer networks (mentioned in the discussion as a new research avenue).

The number of ones in the matrix in Table 6 is 20. In general, if the number of micro-borrowers is n, then the number of ones in the adjacency matrix is $2n$. Moreover, if $n = 2$, the number of paths of length 2 is given by the following power matrix:

$$M^2 = M \times M = \begin{pmatrix} 0 & 1 & 1 \\ 1 & 0 & 0 \\ 1 & 0 & 0 \end{pmatrix} \times \begin{pmatrix} 0 & 1 & 1 \\ 1 & 0 & 0 \\ 1 & 0 & 0 \end{pmatrix} = \begin{pmatrix} 2 & 0 & 0 \\ 0 & 1 & 1 \\ 0 & 1 & 1 \end{pmatrix},$$

whilst the paths of length 3 are shown by the following matrix:

$$M^3 = M^2 \times M = \begin{pmatrix} 2 & 0 & 0 \\ 0 & 1 & 1 \\ 0 & 1 & 1 \end{pmatrix} \times \begin{pmatrix} 0 & 1 & 1 \\ 1 & 0 & 0 \\ 1 & 0 & 0 \end{pmatrix} = \begin{pmatrix} 0 & 2 & 2 \\ 2 & 0 & 0 \\ 2 & 0 & 0 \end{pmatrix} = 2 \begin{pmatrix} 0 & 1 & 1 \\ 1 & 0 & 0 \\ 1 & 0 & 0 \end{pmatrix}.$$

In general, the following law applies:

$$M^s = \begin{cases} n^{\frac{s}{2}} M^2 & \text{if } s \text{ is even,} \\ n^{\frac{s-1}{2}} M & \text{if } s \text{ is odd,} \end{cases}$$

where

$$M = \begin{pmatrix} 0 & 1 & \cdots & 1 \\ 1 & 0 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 1 & 0 & \cdots & 0 \end{pmatrix}$$
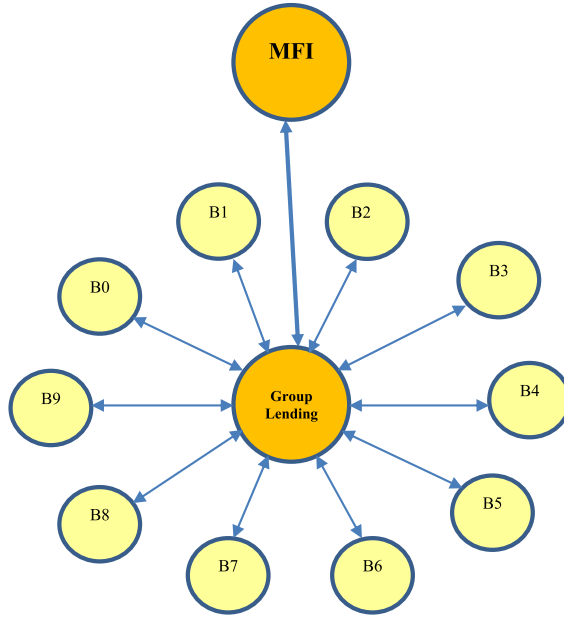
Fig. 5. Group lending with 10 micro-borrowers.

and

$$M^2 = \begin{pmatrix} n & 0 & \cdots & 0 \\ 0 & 1 & \cdots & 1 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 1 & \cdots & 1 \end{pmatrix}.$$

(B) Case of a group lending

Case (A) may be compared with a similar one (see Fig. 5) where micro-borrowers coalesce around a group lending platform that is related to the MFI. Group lending can be defined as a lending mechanism that allows a group of individuals (often called a solidarity group) to provide collateral or loan guarantees through a group repayment pledge. The incentive to repay the loan is based on peer pressure: If one group member defaults, the other group members make up the payment amount. This shows the difference between individual lending and group lending.

In this case, by considering that the relationship between each micro-borrower and the rest of the micro-borrowers and the MFI is bilateral due to the intermediation role of the group lending node (that intermediates funds and data between each micro-borrower and the MFI), the adjacency matrix is represented in Table 7.

The number of ones in the matrix in Table 7 is 110. In general, if the number of micro-borrowers is n, then the number of ones in the adjacency matrix is

$$(n+1)^2 - (n+1) = (n+1)[(n+1)-1] = n(n+1).$$

Let p_i be the probability that borrower B_i repays 1 EUR. If the amount due by borrower B_i is C_i, then the probability that this borrower can repay his/her entire debt is $p_i^{C_i}$. Therefore, the probability that borrower B_i defaults is $1 - p_i^{C_i}$ and, consequently, the probability that any of the borrowers composing the group lending can take care of some solidarity payments is $(1 - p_1^{C_1})(1 - p_2^{C_2}) \cdots (1 - p_n^{C_n})$. Finally, the probability that the group lending can take care of some payments is $1 - \prod_{i=1}^{n}(1 - p_i^{C_i})$, which represents the solvency added by the group lending.

(C) Risk of default

The default risk is a crucial variable both in traditional microfinance schemes (with either individual borrowers or group lending) and when crowdfunded value chains are introduced. Reduction in the risk of default improves loan repayment which, in turn, increases the convergence towards SDGs and the prosocial targets.

Consider a traditional MFI which promotes the potential participation of n micro-borrowers. A measure of the *risk of default* can be determined by the following expression:

$$H = -\sum_{i=1}^{n} p_i \log_2 p_i,$$

where p_i is the probability that the ith microloan is repaid by the corresponding borrower. However, in a microloan within a lending group, due to the solidarity among its micro-participants, the probability p_i increases until $p_1' > p_i$. Therefore, the entropy is now

$$H' = -\sum_{i=1}^{n} p_i' \log_2 p_i'.$$

Entropy is the measure of the disorder or randomness of a system. The entropy of a system X with n possible components whose probabilities are $p_1, p_2, \ldots, p_n$, is given by the following expression:

$$H(X) = -\sum_{i=1}^{n} p_i \log_2 p_i.$$

For values of p_i high enough, one has $H' < H$, as expected, the risk of default decreases. Consequently, the reduction of the risk of default leads to a diminishing of the interest rate which gives rise to an increase in investments at the microfinance level.

5.2.1.2. Crowdfunded microloans

Crowdfunded microloans represent an "augmented" dimension of traditional microloans, examined above in Sec. 5.2.1.1. Consistently with the basic case, they are divided into two main categories [individual loans (A) and group lending (B)] and incorporate the risk of default (C).

As formerly indicated, in a new conception of microfinance, the MFI posts the information about its n micro-borrowers by using a digital platform in such a way that potential micro-lenders can participate as funders of one or more micro-borrowers. This novel financial instrument is called a *crowdfunded microloan* and the micro-lenders are also called *crowd-funders.*

In this case, as the MFI acts as a financial intermediary, each microloan needs at least one crowd-funder able to fund the posted micro-project. Therefore, if k denotes the average number of crowd-funders necessary to fund a standard micro-project, the total number of crowd-funders will be kn, where $k = k(n) > 1$ is a function of n.

(A) Case of individual lending and crowdfunding

Crowdfunding digital platforms add value to the whole microfinance ecosystem thanks to their networking properties (Possega *et al.* 2015). Network theory analysis (Barabási 2016) produces a mathematical measurement of the degree of the nodes (number of links with other nodes), and a consequent estimate of their economic value. The application of this methodology to crowdfunding platforms is innovative.

Figure 6 shows a hypothetical example of a crowdfunded microloan, where crowd-funders C_{11}, C_{12}, and C_{13} lend their money to micro-borrower B_1; crowd-funders C_{21}, C_{22}, C_{23}, and C_{24} lend their money to micro-borrower B_2; and crowd-funders C_{31} and C_{32} lend their money to micro-borrower B_3. In general, C_{ij} denotes the crowd-funder $\#j$ of borrower $\#i$ (B_i). As indicated, each micro borrower's project is posted on the
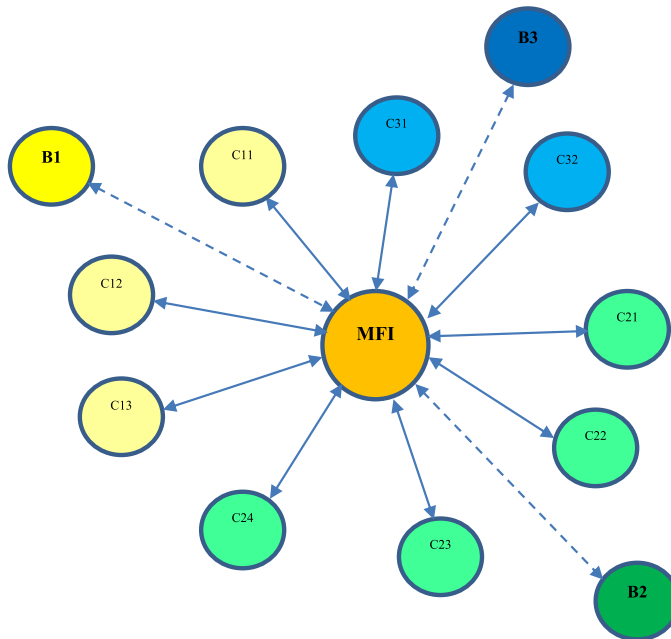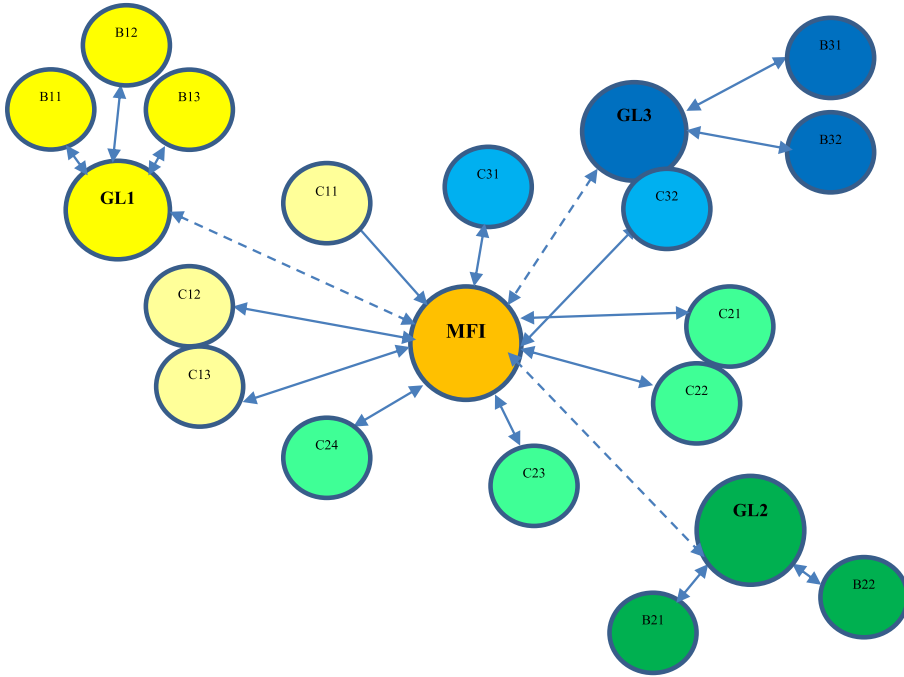

Fig. 6. A crowdfunded microloan.

Fig. 7. A crowdfunded microloan.

lending platform and then potential crowd-funders lend their money for funding this specific project (yellow, green, or blue, respectively). In this network, micro-borrowers (B_1, B_2, and B_3) represent again an individual lending target.

Figures 6 and 7 represent hypothetical cases that illustrate our reasoning.

In this case, the adjacency matrix is represented in Table 8 (observe that the MFI disappears in this matrix because now it plays the role of an intermediary and, consequently, it does not provide any money or information):

In the matrix in Table 8, $k = 3$, and the number of ones is 54. In general, if the number of micro-borrowers is n, then the number of ones in the adjacency matrix is $2kn^2$. Thus, the multiplier (m) of the complexity of the microloan system, in case (A), is

$$m := \frac{2kn^2}{2n} = kn.$$

In our example, the multiplier is $m = 9$.

(B) Case of several group lending and crowdfunding

This case is represented in Fig. 7.

In this case, the adjacency matrix would be Table 9.

Observe that, in Table 9, the number of ones is 24. In general, if there are h group lenders GL_1, GL_2, ..., GL_h with $n_1, n_2, \ldots, n_h$ micro-borrowers, then the number of

Table 8. Adjacency matrix corresponding to Fig. 6.

Nodes	B_1	C_{11}	C_{12}	C_{13}	B_2	C_{21}	C_{22}	C_{23}	C_{24}	B_3	C_{31}	C_{32}
B_1	0	1	1	1	0	1	1	1	1	0	1	1
C_{11}	1	0	0	0	1	0	0	0	0	1	0	0
C_{12}	1	0	0	0	1	0	0	0	0	1	0	0
C_{13}	1	0	0	0	1	0	0	0	0	1	0	0
B_2	0	1	1	1	0	1	1	1	1	0	1	1
C_{21}	1	0	0	0	1	0	0	0	0	1	0	0
C_{22}	1	0	0	0	1	0	0	0	0	1	0	0
C_{23}	1	0	0	0	1	0	0	0	0	1	0	0
C_{24}	1	0	0	0	1	0	0	0	0	1	0	0
B_3	0	1	1	1	0	1	1	1	1	0	1	1
C_{31}	1	0	0	0	1	0	0	0	0	1	0	0
C_{32}	1	0	0	0	1	0	0	0	0	1	0	0

Table 9. Adjacency matrix corresponding to Fig. 7.

Nodes	GL_1	B_{11}	B_{12}	B_{13}	GL_2	B_{21}	B_{22}	GL_3	B_{31}	B_{32}
GL_1	0	1	1	1	0	0	0	0	0	0
B_{11}	1	0	1	1	0	0	0	0	0	0
B_{12}	1	1	0	1	0	0	0	0	0	0
B_{13}	1	1	1	0	0	0	0	0	0	0
GL_2	0	0	0	0	0	1	1	0	0	0
B_{21}	0	0	0	0	1	0	1	0	0	0
B_{22}	0	0	0	0	1	1	0	0	0	0
GL_3	0	0	0	0	0	0	0	0	1	1
B_{31}	0	0	0	0	0	0	0	1	0	1
B_{32}	0	0	0	0	0	0	0	1	1	0

ones in the adjacency matrix is

$$\sum_{j=1}^{h}[(n_j+1)^2-(n_j+1)]=\sum_{j=1}^{n}n_j(n_j+1).$$

(C) Case of a group lending and crowdfunding

In this case, the number of ones in the adjacency matrix can be determined by the same formula as in case (B) in Sec. 5.2.1.1.

(D) Credit risk

Consider a traditional MFI which promotes the potential participation of n micro-borrowers. A measure of the credit risk can be determined again by the *entropy* of the system which is given by the following expression:

$$H=-\sum_{i=1}^{n}p_i\log_2 p_i,$$

where now p_i is the probability that the ith microloan is granted by the MFI. It is well known that the entropy represents the uncertainty of a system, in this case, the

Table 10. Relationship among the numbers of borrowers and lenders and the class of risk.

			Risk of	
			Default	Credit
Number of...	Borrowers	Increases	Decreases	—
		Decreases	Increases	—
	Lenders	Increases	—	Decreases
		Decreases	—	Increases

credit risk of the system is composed of the MFI and the group of micro-borrowers. However, in a crowdfunded microloan, there are k crowd-funders for each microloan which makes that the probability p_i increases until $p_i^{1/k} > p_i$. Therefore, the entropy is now

$$H'' = -\sum_{i=1}^{n} p_i^{1/k} \log_2 p_i.$$

For values of p_i high enough, one has $H'' < H$, as expected, the incertitude (credit risk) associated with the system (microloan) decreases as the number of micro-lenders increases. For example, in the sample of crowdfunded microloans managed by Kiva and described in Sec. 5.1, the average value of k is 21.02. This figure supposes a huge increment in the probability of granting a microloan.

As the risk of default is associated with the number of borrowers and the credit risk is linked to the number of lenders, the corresponding results are determined as summarized in Table 10. The risk of default is inversely proportional to the number of borrowers, and the credit risk is inversely proportional to the number of lenders. This is due to diversification gains that could be acknowledged in the Kiva crowd-funding model.

Table 10 illustrates how the risks of default and credit (affecting borrowers and lenders, respectively) diminish as the numbers of borrowers and lenders increase. So, it serves to demonstrate that the measure of both risks (according to the above formula) is accurate.

5.3. *Proposal of a multiplier by field partners in microloans*

As previously indicated, the insertion of field partners in crowdfunded microloans supposes an increase in the volume of granted microloans and, consequently, an increment in the volume of business of micro-borrowers. Additionally, through these combined instruments, lots of micro-lenders (crowd-funders) satisfy their need to collaborate in the development of the so-called social economy.

Previous discussions in Sec. 5.1, (C) in Sec. 5.2.1.1, and (D) in Sec. 5.2.1.2 have quantified the variations of the prosocial impact, risk of default, and credit risk, respectively, associated with the inclusion of field partners in crowdfunded

microloans. Assuming that these three measures are independent, an aggregate indicator (denoted as m) could be built in the following way:

$$m := (1 + r) \times \frac{H}{H'} \times \frac{H}{H''},$$

with r being the ratio defined in Sec. 5.1. This indicator will be called the *multiplier* associated with the presence of a field partner in crowdfunded microloans. A multiplier is fully consistent with the scalable properties of digital crowdfunding platforms.

The multiplier m can be greater than, equal to, or less than 1. Thus, if $m > 1$, there is value creation; if $m = 1$, there is no value creation; and, finally, if $m < 1$, there is a loss of value in the involved economy.

6. Discussion

The most diffused microloans by sector of activity, shown in Table 3, are often related to a higher number of SDGs (Agriculture, Food, Clothing, etc.), even if this is not always the case. Education, transportation, construction, and manufacturing show high SDG scoring with a low number of microfinance loans. This could indicate new financing priorities, reducing the information asymmetries that prevent optimal allocation from Kiva sponsors (crowd-funders) to micro-borrowers, as shown in Fig. 3.

Goal setting, consistent with SDG scoring, and coordination (mastered by architectural networking) are effective mechanisms to increase prosocial behavior in teams (Chen *et al.* 2017).

A further purpose of this theoretical paper is to introduce a tool (i.e. an indicator) to measure the value added by a field partner (i.e. a microfinance institution) in the economic system where the partner moves on. So, in this context, it does not make sense to test any hypothesis, specifically due to the absence of data on default and credit risks in these contexts.

The findings of this study can be corroborated by consistent literature.

Despite the crucial role that field partners play in this sort of microcredit through online platforms, such as Kiva (Gosh & Vachery 2016), there is a lack of specific literature review about it. Mahajan & Srivastava (2019) show that the inexorable rise of the Internet has given traditional microlending facilities a new online platform where people from any part of the world can lend their money to those in need of it. With the risk of default being tremendously high in comparison to traditional financing, there is an utmost need for the platform to be transparent and trustworthy.

Mahajan and Srivastava (2019) propose a model which is based on blockchain technology and uses a holistic rating system to rate both the borrower and lender instead of the generally used rating of the MFIs or field partners, which act as intermediaries and have a tie-up with the online peer-to-peer platforms nowadays.

Paruthi *et al.* (2016) specify how highly rated field partners drive more lending activities and how different aspects like gender and other features play a role in lending activities. Moreover, they also outline that team lending behavior is willing to take a greater risk than individuals.

Armstrong *et al.* (2018) show that Kiva plays a connector role in the microfinance ecosystem by directly linking funders with borrowers; this type of business model is popularly known as person-to-person lending. The intermediating role of field partners is also explained by Ly & Mason (2012), who show that Kiva assigns a risk rating, from one star to five stars to each of its field partners, considering financial sustainability and reliability.

Ibrahim & Verliyantina (2012) illustrate that the role of field workers is to:

(1) examine the feasibility of SMEs;
(2) calculate the amount of loan required;
(3) collect entrepreneur stories, pictures, and loan details and upload them to the system;
(4) provide the training and knowledge required by the SME entrepreneur.

Galak *et al.* (2011) show that lenders favor individual borrowers over groups or consortia of borrowers, a pattern consistent with the identifiable victim effect. The discrimination between individual lending and group lending represents a key and trendy distinction in microfinance evolution. Field partner risk rating also speaks to the creditworthiness of the borrower, an issue important in person-to-person lending literature.

Other variables such as loan term and field partner risk rating affected the loan value. Burtch *et al.* (2014) show that lenders do prefer culturally similar and geographically proximate borrowers.

Choo *et al.* (2014) show that lending teams are generally more careful in selecting loans by the loan's geo-location, borrower's gender, field partner's reliability, etc. when compared to lenders without team affiliations.

Figueroa-Armijos & Berns (2021) show that entrepreneurs using field partner institutions (e.g. microfinance institutions) specifically tailored to serve vulnerable populations will be better positioned to garner attention from prosocial crowd-funders.

Third-party actors who endorse the entrepreneurial project provide a valuable asset for both investors and entrepreneurs alike (Massa Saluzzo & Alegre 2021). In our context, they may well be represented by field partners.

This study goes beyond the extant literature since it shows that the value added by field partners in the context of crowdfunded microloans can be divided into their prosocial impact through the fulfillment of the well-known SDGs and the variations of the risk of default and the credit risk, both considered as the main purely financial parameters associated with the microcredit operations. The novel theoretical model proposed in this study cannot be calibrated due to the absence of data on default and credit risks in these contexts. Of course, both risks can be considered independent.

If this is a concern, we propose to find a more accurate relationship between both risks by using copulas. Whenever data become available, an update of this study will be possible.

A network theory interpretation is original, as it provides mathematical tools for innovative analysis of the relationships described in Figs. 3–7. Frontier research may consider dynamic networks, where the relationships among connected nodes (crowd-funder, their digital platform, the MFI, group lenders or individuals as micro-borrowers, etc.) change over time.

Furthermore, multilayer networks (Bianconi 2018) where nodes exist in separate layers, representing different forms of interactions, are fully consistent with the main bridging nodes of this case (the crowdfunding platform and the MFI, illustrated in Fig. 3). Multiplex networks (where the bridging nodes coexist) and their evolving dynamics, fostered by digital scalability, may so represent a further analytical tool.

We have wondered whether the gender of crowdfunded micro-borrowers (Strøm *et al.* 2022) is related to the main features that define the quality of a microloan: amount, term, number of lenders, repayment system, and period of lenders' recruitment. By using the multinomial logit regression, we have shown that amount, term, repayment method, and recruitment period indicate that women are the best borrowers. These findings provide useful indications to improve financial inclusion and outreach, consistently with the Sustainable Development Goals.

The role of gender in crowdfunding and microfinance (Gray & Zhang 2017) deserves, however, further investigation, also considering that most microfinance borrowers are women. This could inspire a further research avenue.

7. Conclusion

This study provides a novel indicator of the value added to the economic system where a field partner (i.e. a microfinance institution) is operating. The paper introduces a theoretical model which, unfortunately, cannot be calibrated due to the absence of data on default and credit risks in these contexts. Of course, both risks can be considered independent. If this is a concern, we propose to find a more accurate relationship between both risks by using copulas — a multivariate cumulative distribution function.

This paper has dealt with crowdfunded microloans where field partners have played the role of agents able to "securitize" microloans. Thus, field partners have been considered the "meeting point" of the converging interests of both micro-borrowers and micro-crowd-lenders. Thanks to the crowdfunding scheme (exemplified in Fig. 3), micro-borrowers can easily obtain the microloan they need for developing their business initiatives and, in the case of belonging to a group, they can obtain some economic help for repaying their joint microloans.

On the other hand, micro-lenders are people very sensitive to the development of a social economy and share homophily with the ultimate borrowers. Thus,

the securitization of microloans facilitates their participation in these "prosocial" initiatives by contributing modest amounts.

The main contribution of this study has been the proposal of a global indicator — a multiplier associated with the presence of field partners in crowdfunded microloans — which is a function of the variations of social impact, risk of default, and credit risk in microloans funded by a field partner. This indicator so provides a measure of the increase or decrease of the volume of microloans, as a function of the efficiency of the field partner involved in the crowdfunded microloan.

Network theory analysis, conducted with a graphical representation of the different networks along with a digital supply and value chain, and their adjacency matrices, shows how increased networking — linking crowd-funders to micro-borrowers — adds value, especially if the interacting edges between any two nodes vehiculate richer information (thanks to the intermediating role of field partners) and smarter transactions, ignited by the Kiva model.

Considering the political implications, field partners play a decisive role in the progress and fair development of crowdfunded microloans when matching the legitimate interest of both micro-borrowers and micro-lenders. For these reasons, political authorities of undeveloped and developing countries must promote and monitor the activities of these economic agents to guarantee a credit multiplier greater than one. In this way, further research may determine the multipliers associated with field partners operating in specific economic sectors exemplified by the Kiva community.

Financial inclusion externalities suggested by the on-field application of the model proposed in this study can foster ESG adoption, consistently with SDGs. This may ignite a virtuous spiral, where all the involved stakeholders coalesce around win–win targets, with a common aim to combat everywhere poverty and inequalities.

Conflict of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

R. Aggarwal, J. W. Goodell & L. J. Selleck (2015) Lending to women in microfinance: Role of social trust, *International Business Review* **24**, 55–65.

F. Allen, X. Gu & J. Jagtiani (2021) A survey of fintech research and policy discussion, *Review of Corporate Finance* **1** (3–4), 259–339.

M. F. Alsayegh, R. A. Rahman & S. Homayoun (2020) Corporate economic, environmental, and social sustainability performance transformation through ESG disclosure, *Sustainability* **12**, 3910.

A. H. Anglin, J. C. Short & A. F. McKenny (2020) Third-party signals in crowdfunded microfinance: The role of microfinance institutions, *Entrepreneurship Theory and Practice* **44**, 623–644.

M. Antoncic, G. Bekaert, R. V. Rothenberg & M. Noguer (2020) Sustainable investment — Exploring the linkage between alpha, ESG, and SDGs. SSRN Working Paper, https://ssrn.com/abstract=3623459.

K. Armstrong, M. Ahsan & C. Sundaramurthy (2018) Microfinance ecosystem: How connectors, interactors, and institutionalizers co-create value, *Business Horizons* **61** (1), 147–155.

L. Attuel-Mendes (2016) Crowdfunding and crowdmicrofinance, an evolution of models for entrepreneurship of the poor, *Open Access Library Journal* **3**, 1–7.

A. Barabási (2016) *Network Science*. Cambridge: Cambridge University Press.

P. Belleflamme, T. Lambert & A. Schwienbacher (2013) Individual crowdfunding practices, *Venture Capital: An International Journal of Entrepreneurial Finance* **15** (4), 313–333.

J. P. Berns, M. Figueroa-Armijos, S. P. da Motta Veiga & T. C. Dunne (2020) Dynamics of lending-based prosocial crowdfunding: Using a social responsibility lens, *Journal of Business Ethics* **161** (1), 169–185.

J. P. Berns, A. Z.M. Shahriar & L. A. Unda (2021) Delegated monitoring in crowdfunded microfinance: Evidence from Kiva, *Journal of Corporate Finance* **66**, 101864.

G. Bianconi (2018) *Multilayer Networks: Structure and Function*. Oxford: Oxford University Press.

G. Burtch, A. Ghose & S. Wattal (2014) Cultural differences and geography as determinants of online prosocial lending, *MIS Quarterly* **38** (3), 773–794.

R. Chen, Y. Chen, Y. Liu & Q. Mei (2017) Does team competition increase pro-social lending? Evidence from online microfinance, *Games and Economic Behavior* **101**, 311–333.

J. Choo, D. Lee, B. Dilkina, H. Zha & H. Park (2014) To gather together for a better world: Understanding and leveraging communities in micro-lending recommendation. In: *Proceedings of the 23rd International Conference on World Wide Web*, pp. 249–259.

G. Dorfleitner, E. M. Oswald & R. Zhang (2021) From credit risk to social impact: On the funding determinants in interest-free peer-to-peer lending, *Journal of Business Ethics* **170**, 375–400.

M. Figueroa-Armijos & J. P. Berns (2021) Vulnerable populations and individual social responsibility in prosocial crowdfunding: Does the framing matter for female and rural entrepreneurs? In: *Proceedings of the 54th Hawaii International Conference on System Sciences*.

J. Galak, D. Small & A. T. Stephen (2011) Microfinance decision making: A field study of prosocial lending, *Journal of Marketing Research* **XLVIII**, S130–S137.

M. Gray & B. Zhang (2017) Crowdfunding: understanding diversity. In: *Handbook on the Geographies of Money and Finance* (R. Martin & J. Polard, eds.), 580–609. Cheltenham, UK: Edward Elgar.

N. Ibrahim & Verliyantina (2012) The model of crowdfunding to support small and micro businesses in Indonesia through a web-based platform, *Procedia Economics and Finance* **4**, 390–397.

S. Khavul (2010) Microfinance: Creating opportunities for the poor?, *The Academy of Management Perspectives* **24** (3), 58–72.

Kiva (2020) Due diligence for field partner loans. Online Article, https://www.kiva.org/about/due–diligence/field-partner-role.

M. Kukk & L. Laidroo (2020) Institutional drivers of crowdfunding volumes, *Journal of Risk and Financial Management* **13**(12), 326.

X. Luo, L. Ge & C. Wang (2022) Crowdfunding for microfinance institutions: The new hope?, *MIS Quarterly* **46**(1), 373–400.

P. Ly & G. Mason (2012) Competition between microfinance NGOs: Evidence from Kiva, *World Development* **40** (3), 643–655.

Y. Mahajan & S. Srivastava (2019) Holistic credit rating system for online microlending platforms with blockchain technology. In: *SSCC 2018: Security in Computing and Communications* (S. Thampi, S. Madria, G. Wang, D. Rawat & J. Alcaraz Calero, eds.), Communications in Computer and Information Science, Vol. **969**, 605–616. Singapore: Springer.

F. Massa Saluzzo & I. Alegre (2021) Supporting entrepreneurs: The role of third-party endorsement in crowdfunding platforms, *Technological Forecasting and Social Change* **162**, 120402.

S. C. Moenninghoff & A. Wieandt (2012) The future of peer-to-peer finance. SSRN Working Paper, https://ssrn.com/abstract=2439088.

M. Moleskis & M. A. Canela (2016) Crowdfunding success: The case of Kiva.Org. IESE Business School Working Paper No. 1137-E, https://ssrn.com/abstract=2769841.

R. Moro Visconti, S. Cruz Rambaud & J. López Pascual (2020) Sustainability in FinTechs: An explanation through business model scalability and market valuation, *Sustainability* **12**, 10316.

R. Moro Visconti (2021) *MicroFinTech Expanding Financial Inclusion with Cost-Cutting Innovation.* Cham: Palgrave Macmillan.

F. G. Paruthi, S. E. Frias-Martinez & T. V. Frias-Martinez (2016) Peer-to-Peer microlending platforms: characterization of online traits. In: *Proceedings of the 2016 IEEE International Conference on Big Data.*

O. Possega, M. P. Zylka & K. Fischbach (2015) Collective dynamics of crowdfunding networks. In: *Proceedings of the 48th Hawaii International Conference on System Sciences*, https://www.researchgate.net/publication/274077623_Collective_Dynamics_of_Crowdfunding_Networks.

R. Strøm, B. D'Espallier & R. Mersland (2022) Female leaders and financial inclusion: Evidence from microfinance institutions, *Review of Corporate Finance*, in press.

M. J. Uddin, G. Vizzari, S. Bandini & M. O. Imam (2018) A case-based reasoning approach to rate microcredit borrower risk in online Kiva P2P lending model, *Data Technologies and Applications* **52** (1), 58–83.