Achieving double bottom-line performance in hybrid organisations. A machine learning approach

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March 27, 2023

Note that this is the open-access version of the paper. The final version of the paper will be published in the Journal of Business Ethics

Abstract

Drawing on a global sample of microfinance institutions (MFIs), this paper offers insights into the trade-off versus synergy debate of adopting multiple institutional goals in hybrid organisations. Additionally, it unravels which organisation- and country-specific determinants associate with top joint performance using machine learning techniques. We find that the synergy versus trade-off debate is not dichotomous. Rather, MFIs can be strong both socially and financially but not while charging low interest rates. In our sample, 17% of MFIs serve a low-income clientele in need with a diverse range of services while remaining financially sustainable and ask a close-to-average interest rate. These organisations are larger and more mature as well as financially prudent in that they minimize both financial and credit risk. Moreover, they are located in countries where their services can create larger benefits regarding their underlying goals.

Keywords— Hybrid organisations, social enterprise, microfinance, different underlying goals

1 Introduction

The market for social and environmental responsible firms grows every day. The total assets under management of these firms grew from 8.7 trillion USD in 2016 to 12 trillion USD in 2018 in the United States alone (USSIF, 2018). These companies are also known as hybrid organisations, i.e., enterprises that attempt to pursue two different underlying goals. The most wellknown kind of hybrid organisations are social enterprises (Dees & Elias, 1998), combining social and financial goals (Pache & Santos, 2013). In general, these organisations aim to create a financially viable or even profitable mission-driven business, serving clients while remaining self-sustainable. Social enterprises either emerge from the nonprofit sector as grant-dependent charities and gradually change into income-generating enterprises (Defourny & Nyssens, 2010) or they are spinoffs or joint-ventures of multinational companies that implement an ESG-oriented (environmental, social and governance) objective to produce long term social value (Gilberthorpe et al., 2016; Yunus et al., 2010; Battilana, 2018)[1].

One major debate in the context of hybrid organisations is whether two or more corporate bottom-line goals, such as optimal social and financial performance, are competing or rather complementary (Nicholls, 2010). The results of individual studies vary widely and the nature of the relationship depends highly on the industry (Baird et al., 2012) and the examined company characteristics(Reichert, 2018; Rowley & Berman, 2000; Waddock & Graves, 1997). Several studies predict a trade-off between the underlying goals (Griffin & Mahon, 1997) or mission drift (in social enterprises) when the focus gradually tilts towards pursuing the financial goal (Ben-Ner, 2002; Grimes et al., 2019; Mersland & Strøm, 2010; Postelnicu & Hermes, 2018). Others argue that both goals can reinforce each other, thereby creating synergies or a win-win situation between these seemingly opposing goals (Van Beurden & Gössling, 2008; Jay, 2013; Orlitzky et al., 2003). This paper departs from the premise that the realisation of the trade-off versus synergy outcome depends on the dimensions quantifying the underlying goals and the characteristics of the hybrid organisation itself. Therefore, our paper first explores the relationship between the different underlying goals in hybrid organisations. Then, we identify the company-and country-specific characteristics of being successful in all their goals. The identified influential characteristics of top performing hybrid organisations could then serve as guidelines on how different goals can be institutionalised (Battilana & Dorado, 2010; Heeks et al., 2020), i.e., embedded within the enterprise.

We use a sample of microfinance institutions (MFI), i.e., providers of financial services to low income populations (Yunus et al., 2010), as examples of social enterprises or hybrid organisations (Battilana & Dorado, 2010; Battilana, 2018; Mumi et al., 2020; Vassallo et al., 2019). They present an interesting setting to investigate the pluralistic bottom-line goal as the reconciliation of social outreach and financial sustainability has been the focal point of debate in this growing industry among both academics and practitioners (Battilana & Dorado, 2010; J. Morduch, 1999). In this paper, we draw on machine-learning (ML) techniques to let the 'data speak' free of any preimposed theory (Kitchin, 2014; Leavitt et al., 2020). Our results indicate that the trade-off versus synergy debate is not dichotomous. Synergies between the social and financial goal can be observed in the sense that microfinance institutions can thrive financially while serving a poor clientele in need with services that fit their requirements. However, a trade-off between both goals arises once an MFI also has to grant its services at low interest rates. In other words, hybrid organisations need to make strategic choices concerning the dimensions they wish to optimise. Besides, organisations that offer a wide range of services to a low-income clientele while remaining financially strong, do not ask excessive but close-to-sample average interest rates. This indicates that these organisations essentially maximize their social performance under a financial sustainability constraint. Furthermore, these MFIs minimise financial and credit risk, are larger and more mature and are located in countries where their services are most needed.

The envisaged contributions to the literature are threefold. First, we employ a multidimensional social performance indicator to quantify social performance. It simultaneously captures the MFI's poverty-focus, social outreach and scope of services[2]. Later on in the paper, we complement these variables with the interest rate charged. As such, we offer an improvement over existing studies which typically employ single-dimensional measures such as average loan size and percentage of female clients proxying for poverty-focus and social outreach respectively. Indeed, the scope of services variable prevents misclassification of MFIs that aggressively push large amounts of small debts (low average loans) onto vulnerable people (high % female clients) as high social performers. We thereby respond to the call of D'Espallier and Goedecke (2019) who argue for the use of multidimensional indices which are more aligned with the industry-notion of social performance.

Second, our model allows us to examine clusters of different combinations of both underlying goals, thereby providing insights in the synergy versus trade-off debate. Accordingly, we add one more dimension to the social goal, namely interest rate charged, to analyse how the results change when the cost of taking a loan is considered as an explicit social performance construct.

Third, we uncover the MFI- and country-specific characteristics in which top performing MFIs[3] thrive. Based on these results, it is possible to determine the most favourable environment and company characteristics to increase the probability of successfully institutionalising both goals. We thereby contribute to the literature on the characteristics of the ideal hybrid organisation/social enterprise (Hudon & Sandberg, 2013). Consequently, we address one of the research questions in Smith et al. (2013) labelled Paradox theory (Jay, 2013), which investigates how paradoxical tensions surface and are managed within an organisation.

The remainder of this paper proceeds as follows. Section 2 provides the reader with a theoretic conceptual framework and explains how this paper fits into the current research literature. The next sections elaborate on the research design and provide a detailed overview of the data used. Section 5 interprets the results of the analysis and the last section concludes.

2 Theoretical framework

Hybrids attempt to create synergies between their different underlying goals, for example, by addressing social (Margolis & Walsh, 2003; Battilana, 2018) or environmental issues (Gamble et al., 2019) through commercial activities (Scherer et al., 2009). However, the underlying goals in hybrids are not always compatible (Davies & Doherty, 2019; Greenwood et al., 2010) and the problem becomes acute if they are exposed to long term pluralism in their goals (Pache & Santos, 2013; Ashta, 2020), for example when mission drift occurs in microfinance institutions (Beisland et al., 2019). At some point, either hybrid tensions become too severe and one goal dominates[4] (DiMaggio & Powell, 1983) or a new hybrid version of the two conflicting missions arises[5] (Greenwood et al., 2010; Higgins et al., 2016), which could lead to new opportunities (Jay, 2013; Doherty et al., 2014; Pache & Santos, 2013). For example, adding social objectives to business as usual can differentiate both the client and investor base and add substantial economic value (Hockerts, 2015). By focusing on one specific industry, namely microfinance, this paper is able to annihilate the concerns of Baird et al. (2012), who state that the relationship between social and financial performance is contingent on the industry.

2.1 Measuring social and financial performance in microfinance

In the literature, scholars debate on whether it is possible to achieve strong social and financial performance simultaneously (Grimes et al., 2019; Mersland & Strøm, 2010; Postelnicu & Hermes, 2018; Van Beurden & Gössling, 2008; Jay, 2013). The outcome of whether scholars support the trade-off or synergy side in the debate often depends on the dimensions used for social and financial performance (Reichert, 2018) and on the social enterprise itself. In the next few paragraphs, we discuss different variables for social and financial performance following the Schreiner (2002)-framework[6] and we hypothesise under which conditions they would lead to trade-offs or synergies between the social and financial goal.

A microfinance institution has one central mission, namely poverty alleviation. Therefore, MFIs could only exhibit excellent social performance if they actively pursue this goal. Consequently, a first variable of social performance should proxy the MFI's poverty-focus. In the literature, the average loan amount[7] proxies the poverty level of the clients (D'Espallier et al., 2017; Wry & Zhao, 2018; Cull et al., 2007), it quantifies the amount a client can borrow which varies with their wealth. Hence, a lower average loan amount indicates that poorer clients are serviced (Olivares-Polanco, 2005). Note that smaller loans often lead to relatively higher operational costs, which could come at the expense of financial performance.

Social performance should also grasp the social outreach of the loan portfolio. In poverty-stricken countries, women are often excluded from participating in financial decision making (Chakrabarty & Bass, 2014; D'Espallier et al., 2011) and women are overly represented among the poorest (Kar, 2012). They less often have the means and time to engage in economic activities. Generally, microfinance institutions strive to aid underserved populations like women, hence the percentage of female clients is often used to capture the MFI's social outreach. Additionally, the portfolio risk also declines with the amount of female clients (D'Espallier et al., 2011) since females are more cautious at selecting their projects (Agier & Szafarz, 2013). Therefore, this measure of social performance may be positively correlated with the MFI's financial performance, all else equal.

Another social dimension, namely the scope of services, quantifies how tailored the products are to the needs of the client, ranging from offering different loan products to savings facilities and additional (financial) services. Although this dimension is mainly neglected in empirical work on microfinance, it is considered an important part of social performance (Schreiner, 2002; Beisland et al., 2020; Cerise SPTF, 2022). Ideally microfinance responds perfectly to the diversity and complexity of the demand for financial services (Guérin et al., 2012). Poor people lend for a number of reasons: to create businesses, to pay for a wedding, to buy consumer goods or to educate their children. We still observe many MFIs who offer only one standard loan product to all clients (around USD 100, repaid over six months and organised with group guarantee). Of course, under such conditions a loan will not be of much benefit to many clients as their needs vary considerably (Collins et al., 2009). Savings facilities, apart from the traditional loan services, are another crucial part of scope of services (and social performance) in MFIs as they allow clients to smooth out their volatile income and limit the effects of expensive events like weddings and funerals (Collins et al., 2009). Lastly, scope of services should also incorporate whether the MFI offers additional financial services, termed plus activities, like financial education or micro-insurance. Plus activities make the client financially stronger and more secure to make optimal financial decisions. In general, a higher scope of services may lead to lower financial performance since it is costly to supply a diverse range of products and services.

One last potential dimension of social performance is the cost of taking a loan, proxied by interest rate charged. Lower interest rates correspond to more affordable loans and therefore are deemed more social. In general, microfinance institutions offer smaller loans with the same fixed costs as their larger counterpart. Therefore, MFIs must charge relatively higher interest rates to cover their operating expenses (Cull et al., 2009). MFIs who want to charge low interest rates might be obliged to deviate from the poorest of the poor as they are too costly to serve, suggesting a trade-off between the social and financial goal (Mosley & Hulme, 1998; Reichert, 2018).

Interest rate charged is a heavily debated measure for social performance. Recently, there is a growing amount of literature who warns that the absolute level of 'annual interest rate charged' is rather uninformative about overall social performance (Harper, 2011; Hudon & Sandberg, 2013; Zetzsche & Dewi, 2018). In the sense that microfinance deals with short-term loans (typically weekly or monthly) in a context of high-yield short-term income. Several studies (Harper, 2011; Hudon & Sandberg, 2013; Zetzsche & Dewi, 2018) highlight that 'fair' levels of interest rates on microloans need to consider the price of the loan in relation to the benefits realised over the same time-period, the cost structure of the MFI and the price of alternative borrowing sources rather than imposing a hard-cap on the level of annual interest rates. Note that smaller short-term loans require relatively higher transaction[8], administration and negotiation costs compared to one big long-term loan (Mersland & Strøm, 2012). Also, the price of the loan should be viewed in relation to the available alternatives, which are often short term unsecured loans offered by a money lender or loan shark.

Multiple authors have called for an accurately quantified social performance indicator (D'Espallier

& Goedecke, 2019; Beisland et al., 2020) which takes into account the spectrum of social performance dimensions. We argue that univariatly using one social performance variable does not guarantee that the microfinance institution is excelling in its social goal. Therefore, this paper uses multiple underlying dimensions (poverty-focus, social outreach, products tailored to the needs of the clients and the cost of taking a loan) simultaneously to quantify the social mission. For example, smaller average loan sizes alone do not necessarily indicate strong social performance (Beisland et al., 2020). Several microfinance institutions also offer larger loans to compensate for the costs associated with delivering small loans to their clients (Armendáriz & Szafarz, 2011). Furthermore, the combination of small loans to mainly women is also not necessarily social. Imagine microfinance institutions who aggressively push small credit on vulnerable groups (women), this could hardly be considered social. The combination of high scope of services (i.e., products tailored to the needs of the client) and high percentage of female clients indicates that people in need are serviced by adapted financial services. Adding low average loan sizes to both high percentage of female clients and high scope of services, entails that a low income clientele in need is helped by services that fit their needs. When social performance also grasps the costs of taking a loan, we capture those MFIs that offer a wide variety of services to poor clients in need while doing so at a low price. We believe that a combination of all these variables might cause a trade-off with the financial performance and potentially a trade-off between the social variables themselves. Therefore, the microfinance institution must make strategic choices in which dimensions they intend to optimise.

The financial dimension helps a microfinance institution to reach its poverty-reduction goal and is often quantified by return on assets (ROA) or financial self-sustainability (FSS)[9]. The former is one of the most common measures to identify the financial success of an enterprise (Hagel et al., 2013; Velte, 2017), including MFIs (Mersland & Strøm, 2009) and the latter is a measure tailored for the microfinance industry where donations are common. Donations plague traditional measures like ROA and make comparison across MFIs troublesome. Thus, the FSS variable adjusts for donations and applies common accounting practises to loan losses thereby assuring a standard and uniform financial measure across a sample of MFIs. Taken together, the FSS quantifies the ability of an MFI to cover its expenses and donations with its revenue. A value of one indicates that the MFI breaks even financially.

2.2 MFI- and country-characteristics and top joint performance

Prior studies have investigated the relationship between MFI characteristics and top social or financial performance. However, it is not clear which variables associate with top joint performance. In the next few paragraphs, we will briefly detail the main findings of the literature.

First, the legal type of a microfinance organisation influences its social and financial performance (Quayes, 2012; Prasenjit & Ambika, 2018). Researchers claim that nonprofit organisations (such as NGO and cooperatives) are more suited to reach excellent social performance (Gupta & Mirchandani, 2020; Quayes, 2012) while bank-like microfinance institutions focus more on the financial side to please their shareholders. Also, the size and age of a microfinance institution might impact performance. Older MFIs are more prone to mission drift (Mersland & Strøm, 2010; Aslam & Hwok-Aun, 2017) but are more efficient (Hermes & Lensink, 2011), while younger MFIs may not yet have institutionalised both goals. Furthermore, larger MFIs can benefit from economies of scale and scope and possibly score better on social performance (Aslam & Hwok-Aun, 2017). Moreover, the location of clients plays a significant role in the performance of microfinance institutions. Although servicing rural clients is more social, they are also costlier to reach (Paxton, 2007).

The funding side of an MFI is also heavily debated in the literature (Cobb et al., 2016; J. J. Morduch, 2006; Hollis & Sweetman, 1998). A strong social policy could attract more investors and donations which strengthens the financial position of the MFIs. Therefore, more funds could be reinvested into the social mission. Furthermore, lending to MFIs supports the sector's development (Cobb et al., 2016). On the other hand, donations diminish the FSS[10] and thus reduce financial performance. In general, a microfinance institution needs enough operational capital to stay afloat and ensure a continuation of its services.

Other than the MFI-specific characteristics of the hybrid organisation, the socioeconomic environment can have an influence on performance (Felicio et al., 2013; Ahlin et al., 2011). In particular, social characteristics, like unemployment rate, the country-specific environment (e.g. GDP per capita) and the governance structure of a country (e.g. level of corruption) and even the language (Golesorkhi et al., 2019) can impact the performance of a hybrid organisation (Rahdari et al., 2016). For example, MFIs located in nations with strong market support pay fewer interests (Cobb et al., 2016) which boosts financial performance and higher unemployment rates lead to lower loan repayment rates which negatively impact financial performance.

In the next sections, we outline and execute our empirical design. First, we use a multidimensional clustering mechanism (self-organizing maps) to investigate how the MFI's hybrid goals coincide using the described social and financial dimensions simultaneously. To this end, we construct a multidimensional social performance measure treated as a latent variable in the clustering exercise. Second, we investigate which MFI- and country-specific variables highlighted in the literature have the highest association with top social and financial performance to uncover the most favourable conditions for hybrid organisations. We test the sensitivity of the results when the interest rate charged is added as an additional social performance construct.

3 Research design

3.1 Constructing a scope of services variable

We extract the scope of services variable as a latent (unobserved) trait using structural equations modelling (SEM) out of its three theoretic components, namely the number of different loan products (LP)[11] and dummies that indicate if the MFI offers savings facilities (SF) or plus activities (PA). SEM is a combination of factor analysis and multiple regression analysis. It does not preimpose the weights of the three different components of scope of services. Afterwards, we check if the constructed weights correspond with the theoretical expectation.

SEM simultaneously estimates three regression equations to pinpoint the value of the unobserved scope of services variable, as shown in Equation (1). As such, there are more equations than unknowns and hence the scope of services variable can be easily estimated.

$$\begin{aligned} PA &= \alpha_1 + \beta_1 \cdot \text{scope} + \varepsilon_1 \\ SF &= \alpha_2 + \beta_2 \cdot \text{scope} + \varepsilon_2 \\ LP &= \alpha_3 + \beta_3 \cdot \text{scope} + \varepsilon_3. \end{aligned} \tag{1}$$

where ε_i is an error term and $\alpha_i, \beta_i \in \mathbb{R}$. The β's represent the correlation between the scope variable and its different aspects. In short, Equation (1) shows that the scope of services causally influences each of its components. Theoretically, we expect that each β is positive because offering more different services should result in higher scope.

3.2 Performance clustering of the microfinance institution

This paper uses self-organising maps (SOM) and k-means clustering[12] to identify different clusters of financial and social performance of MFIs. The process is depicted in Figure 1. Self-organising maps, a type of artificial neural network, were introduced by Murtagh and Hernández-Pajares (1995) and applied in different fields[13] including the microfinance context (Louis et al., 2013). A SOM maps multidimensional observations on a two-dimensional grid using a feed-forward neural network, where similar observations are placed close together and dissimilar observations further apart. It is considered a superior technique in graphing observations using several underlying variables jointly and therefore convenient for interpreting multidimensional data (Murtagh & Hernández-Pajares, 1995; Ralhan, 2018).

We construct two different self-organising maps to investigate the different combinations of social and financial performance and the effect of adding interest rate charged as an additional social performance variable on top of percentage of female clients, the size of the loans and the scope of services offered. The self-organising map will divide the 5- or 6-dimensional data-vectors (FSS, ROA, average loan outstanding scaled per PPP, scope of services, percentage

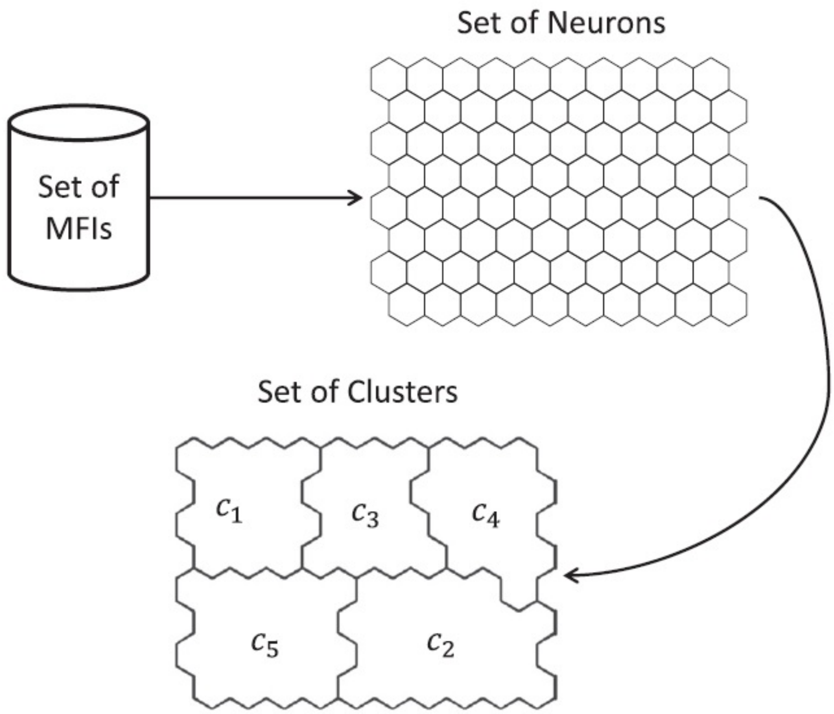


Figure 1: Stepwise representation of the clustering methodology
Notes: Reprinted from "Financial Efficiency and Social Impact of Microfinance Institutions Using Self-Organizing Maps," by P. Louis, A. Seret and B. Baessens, 2013, *World Development, 46*, 197-210. Copyright [2013] by Elsevier.

of female clients and depending on the choice of social dimensions also portfolio yield) in several groups which will be represented by their centroid, also called a neuron. All the neurons together summarise the topology of the data. In each group, the data-vectors are as similar as possible such that the neuron can be seen as a prototype of the data-vectors in its group. Afterwards, the neurons are projected on a two-dimensional space[14]. K-means clustering will provide an extra layer on top of the constructed self-organising map. This algorithm clusters the neurons such that observations in one cluster are as homogeneous as possible. These clusters will form areas with similar properties in terms of social and financial performance. In general, the self-organising map and k-means clustering show different types of clusters of similarly performing MFIs on all underlying dimensions jointly. As a result, it is possible to identify the top performing cluster by looking at the average value per cluster of all the performance measures.

The quality of the self-organising map can be assessed by the mean quantification error (MQE) (Murtagh & Hernández-Pajares, 1995), which is calculated as the average Euclidean distance of each input vector to its closest neuron (the best matching unit), i.e., if the neuron actually represents the data vectors in its group. A small MQE indicates that the SOM represents the topology of the input space.

3.3 Selection of influential features and determination of the direction of association

Once the clusters are constructed through the SOM and k-means clustering, we determine which factors influence the likelihood of harmonising the social and financial goals, where we consider both MFI- and country-specific variables. First, we select the most influential variables by performing a feature selection algorithm. This reduces the dimensionality of the data, the probability of overfitting (Chandrashekar & Sahin, 2014) and training time and it improves accuracy. Then, we characterise how each of the remaining variables influences the dependent variable, namely if a microfinance institution is able to achieve joint top performance in its social and financial goals.

This paper applies extreme gradient boosted trees (XGBoost) (Tianqi Chen & Guestrin, 2016) for feature selection and to characterise how each of the remaining variables influences the dependent together with SHapley Additive exPlanations (SHAP) (Lundberg & Lee, 2017). Xu et al. (2019) show that gradient boosted trees outperform or match other features selection algorithms on several real world data sets. Boosting is a learning algorithm which uses multiple simpler models (so called weak learners) to adaptively fit the data. More specifically, the weak learners used here are regression and classification trees, which partition the sample space in nonoverlapping regions and fit the model to each of these regions. On top of that, the algorithm simultaneously applies multiple tools to prevent overfitting, like L1 and L2 penalties on leaf scores instead of on the features directly (like in Lasso and Ridge regression) (Tianqi Chen & Guestrin, 2016). Hence, it will reduce the impact of redundant features without setting their contributions to zero entirely[15]. Using gradient boosted trees has a number of other important advantages (Hastie et al., 2009; Murphy, 2012). First, it is able to deal with both categorical and continuous data and outliers are dealt with in the methodology. Secondly, tree boosting methods are able to automatically capture nonlinear relationships and high-order interactions within the data, whereas these have to be explicitly modelled in traditional (linear) regression. Lastly, the model is able to deal with large datasets by punishing too complex outcomes while remaining scalable.

4 Dataset and description of the variables

We use a Microfinance Industry dataset maintained by one of Europe's leading research groups on social enterprises and microfinance[16], merged with the governance indicators and some other country-specific variables of the Worldbank. The microfinance-specific features, from the Microfinance Industry dataset, are extracted from institutional and social rating reports gathered by independent rating agencies[17]. Arguably, the dataset is perceived to be better than self-reported data (Mersland & Strøm, 2010) and addresses the self-selection and large-firm bias which is present in the MIX market dataset[18]. The Microfinance Industry dataset covers a wide range of organisational structures, along with social and financial indicators. The fact that MFIs are rated means that the microfinance institutions, which do not have the intention to pursue a double bottom-line objective (social and financial performance), have been filtered out. Moreover, rating data is considered representative for the microfinance industry (Mersland & Strøm, 2009; Hudon & Sandberg, 2013).

Our data sample consists of 40 variables[19] and 342 unique MFIs. Moreover, the locations of the MFIs are spread all over the world and lie in 69 different countries. We winsorise outlying observations of the clustering variables (ROA, FSS, % of female clients, scope of services, loan outstanding average per PPP and portfolio yield) to the 99.9% quantile and 0.1% quantile, leaving a total of 2192 observations. This procedure ensures that the influence of outlying observations is limited[20]. On average each MFI is followed for 6 years in the time period from 1998 until 2015.

The distribution of the final scope variable can be consulted in Table 1[21]. Each line represents one value of the scope of services variable and the corresponding underlying values of its components (number of loan products, savings facilities and plus activities). For example, if the MFI offers one loan type with plus activities, the scope of services variable has a value of -1.427. Note that the resulting scope of services variable becomes higher if the MFI offers more different types of loans, savings facilities and plus activities, in other words the β in Equation (1) are positive, as expected. The number of loan products has the highest influence on the scope of service variable and accounts for the largest 'jumps' in its value. Table A.3 provides different goodness of fit tests for the structural equations model used to construct the scope of services variable (Kline, 2015). All the fit measures indicate that the scope variable is a good fit.

Scope of services	Number of loan products	Savings facilities	Plus activities	Scope of services	Number of loan products	Savings facilities	Plus activities
-1.456	1	0	0	-0.053	4	0	0
-1.427	1	0	1	-0.024	4	0	1
-1.067	1	1	0	0.324	4	1	0
-1.038	1	1	1	0.353	4	1	1
-0.986	2	0	0	0.411	5	0	0
-0.957	2	0	1	0.440	5	0	1
-0.605	2	1	0	0.791	5	1	0
-0.576	2	1	1	0.820	5	1	1
-0.519	3	0	0	0.874	6	0	0
-0.490	3	0	1	0.902	6	0	1
-0.141	3	1	0	1.260	6	1	0
-0.113	3	1	1	1.289	6	1	1

Notes: The left columns indicate the values of the underlying variables (number of loan products, savings facilities and plus activities)

Table 1: Construction of the scope of services variable

In Table 2, we present summary statistics of the social and financial variables and the MFI-specific determinants on the MFI-year disaggregated level. Microfinance institutions mainly give small loans, the average loan amount (PPP adjusted) of the sample is only 425 Dollar in the 3rd quantile. The outreach to women is on average higher than 60%, as reported in Cull et al. (2007), Hermes and Lensink (2011) and Quayes (2012). The scope of services variable is slightly harder to assess since it is built out of eight different dummy variables, a higher value indicates a wider scope. The annualised portfolio yield serves as a proxy for interest rate, most MFIs ask a high interest rate in comparison to larger collateralised loans in regular banks. Approximately 75% of the observations ask an interest rate above 24% per year on a loan. The first quantile of yearly return on assets[22] is already positive and roughly half of the MFI are financially self-sustainable ($FSS > 1$)[23]. The highest correlation between the clustering variables occurs between the return on assets and the financial self-sustainability and is equal to 57.60%[24].

In the feature selection algorithm, we use different MFI-specific variables depicted in Table 2 and Table 3. Regarding the MFI-specific variables, we use those typically included in MFI performance research (Cull et al., 2007; Mersland & Strøm, 2009), i.e., portfolio yield, debt over equity, portfolio at risk over 30 days, loan loss expense rate, size, age, client growth, the market they operate in and their legal type. Furthermore, over 50% of MFIs have at least twice as much debt as equity in a certain year, indicating that most MFIs use debt to fund their operations. Next, we use two different variables to quantify the default cost of an MFI, namely portfolio at risk over 30 days and loan loss expense rate. The logarithm of the assets serves as a proxy for the size of an MFI. This variable has a standard deviation of roughly 1.5 which suggests that the MFIs in our sample are comparable in size. Further, the sample consists of a wide range of ages of MFIs. Some MFIs just started their business, while the oldest MFI already exists for 61 years, illustrating that some MFIs have been lending to low income customers long before Yunus and Grameen Bank started operations in Bangladesh in 1976 (Yunus et al., 2010). Finally, client growth serves as a proxy for MFI growth (Ahlin et al., 2011), as such an MFI grows 17.9% per year on average. Although most MFI grow over time, there are several MFI that shrink in size as the minimum indicates.

	Mean	Std.	Min.	1st Q.	Median	3rd Q.	Max.
PPP-adjusted average outstanding loans	446.631	1041.543	0.010	2.015	64.178	425.012	15851.433
% female clients	0.809	0.219	0.010	0.483	0.609	0.636	1.000
Scope of services	-0.000	0.614	-1.422	-0.518	-0.068	0.379	1.257
ROA	0.029	0.010	-1.200	0.005	0.031	0.069	1.105
FSS	1.041	0.310	0.031	0.876	1.043	1.217	2.500
Portfolio yield	0.369	0.165	0.000	0.246	0.340	0.455	1.277
Debt/equity	4.196	30.384	0.000	0.800	2.000	3.820	1358.600
Par30	0.059	0.084	-0.271	0.014	0.036	0.069	0.973
Loan loss expense rate	0.027	0.061	-0.391	0.006	0.016	0.032	2.066
$\ln(assets)$	15.629	1.493	10.565	14.596	15.519	16.632	19.869
Age	13.947	9.234	0.000	7.000	12.000	18.000	61.000
Client growth	0.394	1.888	-0.915	0.055	0.179	0.401	72.636

Notes: Par30 refers to the portfolio at risk over 30 days and LLER is the loan loss expense rate of the MFI. ln(assets) proxies the size of the MFI.

Table 2: Summary statistics of the financial, social and MFI-specific variables

Table 3 provides the frequency statistics of the legal type and the market where the MFIs operate in. Over half of the observations are located in a mixed urban-rural market, while only 15.4% operates solely in a rural market, potentially due to the costs associated with servicing people in remote areas. Although over 35% of MFIs are profit oriented institutions (NBFI[25] or bank), over 50% of MFIs remain a NGO.

Name	Categories	Frequency	Percentage
Type of market	Urban	565	25.81%
	Rural	337	15.40%
	Urban/Rural	1287	58.79%
Legal Type	Bank	89	4.06%
	NBFI	684	31.25%
	NGO	1050	47.97%
	Cooperative	342	15.62%
	State	14	0.64%
	Other	10	0.46%

Table 3: Description of the dummy Variables

Lastly, Table 4 displays the summary statistics of the governance indicators and other country-specific

	Mean	Std.	Min.	1st Q.	Median	3rd Q.	Max.
Control of corruption	-0.604	0.386	-1.722	-0.844	-0.646	-0.308	0.752
Government effectiveness	-0.500	0.395	-1.761	-0.774	-0.549	-0.178	0.644
Regulatory quality	-0.317	0.460	-1.688	-0.585	-0.286	-0.025	0.757
Political stability	-0.688	0.602	-2.690	-1.013	-0.673	-0.274	1.172
Voice and accountability	-0.304	0.518	-1.749	-0.667	-0.194	-0.085	1.040
Unemployment rate	6.172	4.472	0.317	3.300	4.860	8.130	31.110
Government debt (% GDP)	43.121	24.316	4.000	26.076	38.400	56.000	270.600
GDP per capita (per 1000)	871.267	2879.309	0.742	8.343	26.521	257.841	31950
Growth of GDP	0.112	0.091	-0.985	0.062	0.101	0.140	1.014
Inflation (annual %)	6.496	6.255	-60.496	2.942	5.393	8.484	96.094
Official development aid per capita ($)	43.979	50.948	-10.297	14.555	29.706	59.466	669.216

Table 4: Summary statistics of the country-specific variables

variables of the World Bank to quantify the country-specific elements of the MFI. This paper includes control of corruption, government effectiveness, regulatory quality, political stability, voice and accountability, unemployment rate, government debt, GDP per capita, GDP growth, inflation and official development aid per capita. The governance variables range from -2.5 to 2.5 and most of these variables are negative until the third quantile, meaning that the included countries are more likely to have a weak governance structure. The unemployment rate, expressed in percentage of the labour force, is 6 percentage on average, which is double the unemployment rate of the USA[26]. On the other hand, the average government debt is only one third of the government debt of the USA. Notably, the GDP per capita of the countries under investigation (mostly third world countries) is also much smaller than that of the USA. Most countries in the sample are developing countries with an average GDP growth of 11% per year and over 75% of the countries grow over 6% per year. Despite steady growth, most countries still receive official development aid (ODA). Over 50% of observations receive more than 43 dollar per capita. Note that the minimal value of ODA is negative, indicating that the principle loaned amount (but not the interest) has been repaid.

5 Main results

5.1 Performance Clustering of the Microfinance Institutions

We subsequently present two clustering algorithms that respond to the strategic choices the MFI can make with respect to social performance. In the first one, social performance is proxied by percentage of female clients, average loan size and scope of services. In the second one, we use the same variables but we add interest rate charged as an additional social performance construct.

5.1.1 Clusters based on three different dimensions of social performance

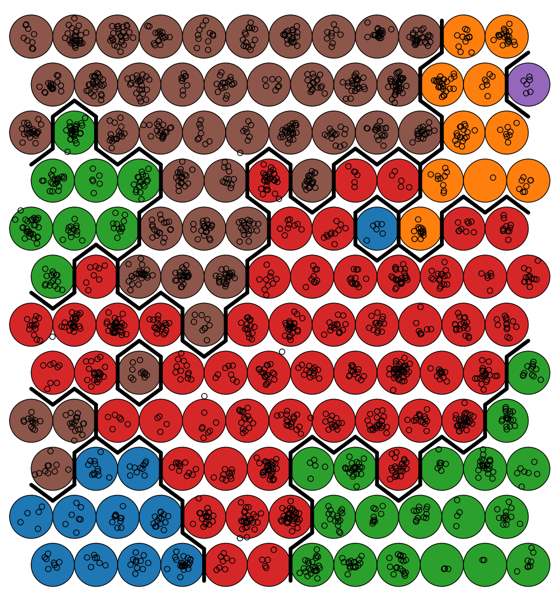
Figure 2 shows a 12 by 12 self-organising map with six different clusters[27], constructed using jointly average loan outstanding (PPP adjusted), percentage of female clients, scope of services, FSS and ROA. Although each cell in the SOM is equally far from its neighbours, it does not contain the same amount of observations. This indicates that some observations are more similar than others. The constructed self-organising map has a mean quantification error (MQE) of 0.5147, which is small and therefore the SOM represents the topology of the input space.

	# obs.	PPP-adjusted outstanding average loans	FSS	ROA	% Female clients	Scope of services	Social	Financial
Green	362	196.437	1.382	0.104	0.828	0.002	++	++
Brown	749	337.655	1.037	0.024	0.479	0.462	+	-
Red	841	227.916	0.965	0.034	0.693	-0.351	-	-
Blue	113	123.862	0.469	-0.229	0.777	-0.279	+	- -
Orange	122	3490.123	1.100	0.040	0.488	-0.158	- -	++
Purple	6	10970.454	1.214	0.034	0.368	-0.150	- -	++

Notes: ++ excellent performance in all indicators, + good performance, - bad performance, - - terrible performance in all indicators[28].

Table 5: Cluster analysis

Table 5 represents the average values of the underlying dimensions per cluster and a strength indicator of financial and social performance (explained in Footnote 28). One important observation



Notes: each circle represents one neuron and the observations are depicted inside each neuron, the clusters are shown in colour.

Figure 2: Cluster plot

is that the green cluster contains 16.51% of the observations and has the best combined values for both social and financial performance in all underlying variables. This indicates that a substantial part of observations are simultaneously top performing on both their social and financial goals with these dimensions. This is somewhat at odds with M. Friedman (2007) and Hermes and Lensink (2011), who predict a trade-off between the two goals. Cull et al. (2009) even state that financial self-sustainability is not reconcilable with helping the poor. The green cluster contains the highest values for the financial performance variables (a ROA of 10.4% and a FSS of 1.382) and the second best or best average values for all the social variables. It has an average loan size of 196 dollar, 83 % female clients, on average 3-4 different types of loans, 54% of the MFIs allow their clients to set up a savings account and 48% also provide plus activities. Although other clusters can excel in one particular dimension, no single other cluster has the best combined values. A more thorough description of the other clusters can be found in the appendix in Section A.6 as well as a stability discussion of our clustering algorithm. In subsection 5.2, we will analyse this green cluster in more detail by investigating which variables associate with top joint performance.

5.1.2 Clusters based on four different dimensions of social performance

We now expand our clustering mechanism by including an additional dimension of social performance, namely interest rate charged. The resulting SOM with portfolio yield, percentage of female clients, scope of services, average loan size, ROA and FSS as clustering variables, has a MQE of 0.688 and contains six clusters[29]. The model fit of this SOM worsened a bit due to the extra variable for social performance.

	# obs.	Loan outstanding average	FSS	ROA	% Female clients	Scope	Interest rate	Social	Financial
1	794	323.04	1.07	0.03	0.59	0.57	0.35	-	+
2	533	159.66	0.76	-0.02	0.70	-0.11	0.28	+	- -
3	8	89.67	0.33	-0.80	0.68	-0.06	0.57	-	- -
4	421	376.6	1.28	0.08	0.53	-0.40	0.37	--	++
5	342	299.48	1.10	0.06	0.82	-0.66	0.58	-	++
6	95	4400.27	1.14	0.04	0.45	0.02	0.27	-	++

Notes: ++ excellent performance in all indicators, + good performance, - bad performance, - - terrible performance in all indicators[28].

Table 6: Cluster analysis

Table 6 depicts the average values of all the underlying variables per cluster. From this table, we clearly observe that the top social and financial performing cluster no longer exists (++ for both social and financial performance). The results indicate that combining low interest rates, good social outreach, offering a high scope of products, issuing small loans and maintaining good financial performance is not reconcilable. Consequently, the combination of all these social indicators and being financially sound is not reconcilable, which is the basic requirement for a hybrid organisation. In other words, the trade-off situation is inevitable when an MFI chooses to optimise its combined financial performance and social performance in terms of loan size, scope of services and percentage of female clients while charging low interest rates.

Furthermore, notice that there does not exist a single cluster that has excellent social performance (++ sign) in all the underlying dimensions. This could indicate that there might be a trade-off between the social dimensions themselves. Cluster two is the only cluster that received a plus sign on social performance by combining low average loan sizes, high percentage of female clients and low interest rates. However, this cluster has a lower scope of services than the sample median and thus could not exhibit excellent social performance in all its dimensions. MFIs in this cluster only offer on average 2 different loan types, 33% offer savings facilities and 59% offer an additional service. Especially the low number of loan products is worrisome, this indicates that it is difficult for clients to find a loan product that will fit their needs.

In summary, it is possible to reconcile top social and financial performance when social performance is regarded as offering a wide scope of financial services to a low income clientele in need. However, the trade-off situation is inevitable when a microfinance institution wants to grant small loans and a high scope of products to a clientele in need while charging low interest rates. In other words, no MFI can be socially and financially strong while offering its products at low interest rates.

5.2 Features associated with joint top performance

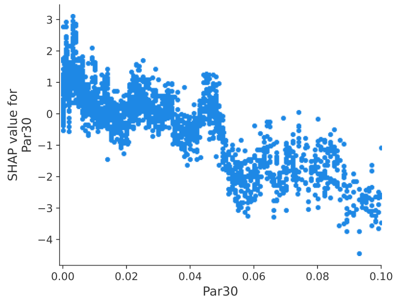
This section uncovers the most influential variables associated with top performing MFIs by using gradient boosted trees (Xu et al., 2019). In other words, we further investigate the green cluster and in particular deepen our understanding of the relationship between interest rate charged and being top performing in the chosen social and financial dimensions.

The gradient boosted trees are trained on 85% of the dataset using the dummy variable ‘joint top performance’ as the dependent variable. Utilising the remaining 15% of the data to check the model accuracy gives an accuracy of 88.15% for the full dataset. By iteratively excluding the least important variable (quantified by the inclusion in boosted trees) and refitting the tree on the remaining variables, the model reaches an accuracy of 87.84% for the top performance model retaining 9 that are most influential for combined social and financial performance.

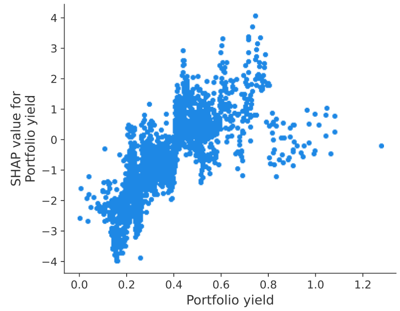
The nine variables retained in the final best-fit model, ordered by importance, are: portfolio-at-risk over 30 days (par30), annualised portfolio yield, debt-to-equity, GDP per capita, the loan loss expense rate (LLER), the logarithm of the total assets, the legal type 'non-bank financial institution (NBFI)', age and the political stability. Note that two of the nine most important variables are country-specific indicators. This means that the institutional environment and not only the structure of the MFI, has an influence on the performance of a microfinance institution, which is in line with previous findings of Ahlin et al. (2011). Furthermore, several variables are not significant to reach a good prediction accuracy according to the gradient boosted tree algorithm. For example, the type of market is not included, this could indicate that the extra cost to reach rural clients is negligible, which is in contradiction with Paxton (2007). Besides, only two of the ten country-specific variables are influential. Possibly, one could argue that the microfinance model has been good in adapting to all kinds of environments.

Figure 3 depicts the relation between all the independent variables and the dependent 'joint top performance'. Our model indicates that the country-specific environment is important, GDP per capita in Figure 3d has the fourth highest influence on the probability of achieving top performance both financially and socially. Figure 3d shows that smaller values of GDP per capita have a positive association with joint top performance. Therefore, top joint performance is associated with microfinance institutions located in countries with low GDP per capita, possibly because the inhabitants of these countries have a higher need for small affordable loans offered by MFIs. In addition, in low GDP per capita countries there is more to gain both financially and socially. The political stability in Figure 3i, on the other hand, is to a lesser extend important to predict top joint performance. Mainly because, the influence of political stability fluctuates around zero, i.e., there is no recognisable pattern. Consequently, successful MFIs can be found in countries with different governance structures demonstrating the adaptability of the microfinance business model.

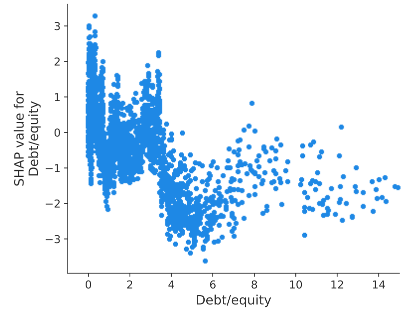
We now turn to the variables quantifying the risk profile of the microfinance institution, namely portfolio-at-risk, debt over equity ratio and loan loss expense rate. First, both default



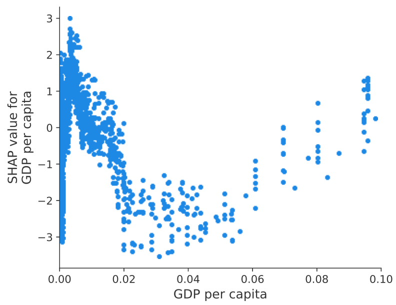
(a) portfolio-at-risk (30 days)



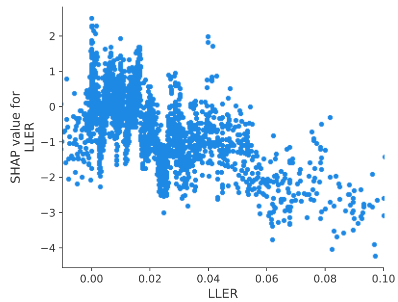
(b) Annualised portfolio yield



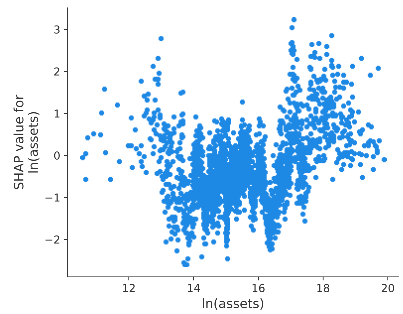
(c) Debt/equity



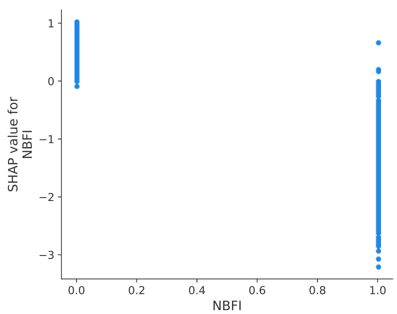
(d) GDP per capita



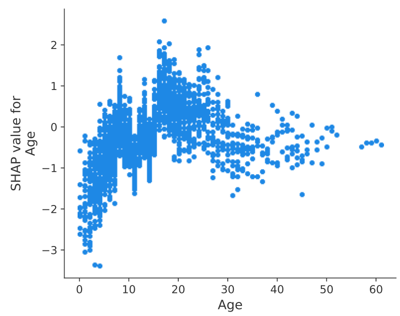
(e) Loan loss expense rate



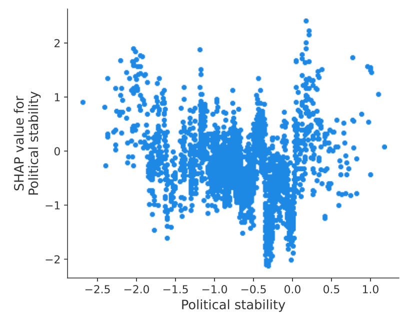
(f) Size proxied by ln(assets)



(g) Legal type: non-bank financial institution



(h) Age



(i) Political stability

Notes: the y-axis denotes the SHAP value per observation, where SHAP stands for SHapley Additive exPlanations (Lundberg & Lee, 2017). It entails how each observation associates with top joint performance. The x-axis gives the range of the variable of interest. Note that each dot represents one observation and the different plots are ranked by influence on top joint performance.

Figure 3: Effect of each variable in the model on probability of success (color Black and White)

cost measures, portfolio-at-risk over 30 days and loan loss expense rate (see Figures 3a and 3e respectively), influence the dependent variable in a similar way, which is as expected as both measures reflect credit risk in an MFI. Both curves exhibit an overall downward quasilinear trend which indicates that a default cost close to zero has a positive influence, while larger default costs negatively associate with joint top performance (Ahlin et al., 2011; Mersland

& Strøm, 2010). Accordingly, controlling risk should remain a priority in microfinance as it has been since inception in the 1970s when microfinance was introduced as an alternative to the many failures of government lending programmes (Hulme & Mosley, 1996). Secondly, Figure 3c shows that a high debt over equity ratio has a negative impact on the probability of being a top performer. The debt-to-equity ratio is on average 29.68 percentage lower for top performing microfinance institutions. Note that organisations funded with debt need to pay funding costs which reduces ROA and FSS. On top of that, an MFI contracting debt needs to make sure that the debt holder will not disturb the focus of the MFI, to retain good social performance. We find that a top performing MFI is financially prudent by mostly financing its operations through retained earnings and a limited number of donations. Donors often do not fund 'financially strong' MFIs since they are already financially sustainable. However, this strategy could limit the further growth potential of the top performing MFIs. Consequently, donors might also consider financially sustainable MFIs, since these could be most qualified to effectively use the funds.

Figure 3f shows that overall the relationship between size (proxied by the logarithm of assets) and top performance has a parabolic shape. However, there are only a limited amount of small observations that have a positive influence on 'joint top performance'. In general, bigger MFIs correlate with joint top performance which is in line with Aslam and Hwok-Aun (2017). They tend to serve a larger client base and have more resources at hand. Thus, larger MFIs are better suited to offer a wide range of products (and thus have a larger scope of services) and more easily adhere to multiple objectives. Both these observations are a result of economies of scale and scope (Hartarska et al., 2010). The age of a microfinance institution also influences the probability of top performance. Figure 3h shows that the relationship between top joint performance and age is inverse U-shaped, only MFIs between 10 and 30 years old have a positive influence on joint top performance. These MFIs show enough maturity to balance top social and financial performance (Prasenjit & Ambika, 2018), which could indicate that MFIs exhibit a learning effect. Younger MFIs have not yet been able to resolve hybrid tensions, while older MFIs could suffer from mission drift (Aslam & Hwok-Aun, 2017; Hermes & Lensink, 2011; Beisland et al., 2019).

Top performing MFIs can be found in any legal type, however, they are less likely to be a non-bank financial institution (NBFI). Figure 3g clearly indicates that being a NBFI has a negative association with joint top performance[30]. These MFIs often focus too much on the financial performance at the expense of the social goals, which could be driven by the fact that NBFIs are owned by shareholders (Mersland, 2009).

Finally, the last feature that has a significant influence on the performance of microfinance institutions is the annualised portfolio yield on loans. The relationship in Figure 3b between portfolio yield and top performance has a quasilinear upward sloping shape. In general, this indicates that higher annualised portfolio yields are associated with top performance both socially and financially. In our sample, top preforming MFIs ask a close-to-average interest rate. This result is in line with Mosley and Hulme (1998), who state that sustainable microfinance institutions have a higher impact and ask a relatively higher interest rate. Moreover, annualised interest rates below 40% are not associated with top joint performance[31]. In other words, relatively higher interest rates on loans are compatible with serving the poorest, offering them a wide variation of products and having strong social outreach[32]. Harper (2011) has since long argued that the cost of a loan should always be compared with the returns of the invested project which is typically high in emerging markets[33]. Moreover, Armendáriz and Morduch (2010) argue that the return on investment is relatively higher for a smaller amount of starting capital. Additionally, poor people prefer easy access to financial services (CGAP, 2002; Dehejia et al., 2012; Hudon & Sandberg, 2013).

6 Conclusion and discussion

The aim of this paper is to investigate the performance mix of the multiple goals of hybrid entities and to unravel both organisation- and country-specific determinants that associate with top performance in all their underlying goals using machine learning techniques. We utilise a sample of microfinance institutions as an example of hybrid organisations. Our results indicate that the synergy versus trade-off situation is not dichotomous. 16.5% of observations achieve top performance in both underlying goals in the sense that these MFIs service a wide variety of low income clients with services that fit their needs while obtaining strong financial performance. However, if the MFIs also need to offer their services at 'low' interest rate, then we observe trade-offs either with the financial side or between the social dimensions themselves. This result indicates that it is not feasible to offer a wide range of financial services in small loan amounts to vulnerable clients, while at the same time charging minimal interest rates and being financially self-sustainable. In other words, hybrid organisations must make strategic choices concerning the dimensions of their underlying goals they wish to optimize.

Furthermore, our gradient boosted tree analysis shows that hybrid organisations need to uphold several structural design features to achieve top performance in the dimensions of their choice. More mature and larger hybrid organisations have an advantage since they have more means and had more learning time to balance both goals. In addition, the location of the hybrid matters in the sense that MFIs can ensure larger benefits with respect to their goals at locations where their services are most needed. In any case, a hybrid must guarantee a stable risk taking regime where they monitor their financial and credit risk. Finally, the legal type of a hybrid might dictate their choices and therefore is important.

An important contribution of this paper is that it includes multiple dimensions for social and financial performance simultaneously to quantify the overall performance of the hybrid entity. Hereby, we construct a new measure of social performance compared to the literature (Cull et al., 2007; Kar, 2012; Wry & Zhao, 2018), namely the 'scope of services'. As such, this paper offers an improved measurement of social performance over univariate proxies and its clustering mechanism is designed to include and investigate more dimensions. This responds to calls for improved multi-dimensional measurement of social performance which is more in line with the industry's notion of client protection (Beisland et al., 2020; D'Espallier &

Goedecke, 2019).

Our findings also provide interesting insights on the trade-off versus synergy debate in hybrid entities, as well as on the role of interest rates in the microfinance industry. We find that MFIs can be strong both financially and socially but not at low interest rates. We note, however, that the top performing cluster (MFIs that offer a wide variety of services to a low-income clientele in need while remaining self-sustainable) does not charge excessive interest rates[34], but close-to-sample average of 36.9%. Hence, these MFIs maximise their social mission under the constraint of financial self-sustainability which is in line with the sustainable finance frame developed in Schoenmaker (2017) as well as with the original double bottom-line microfinance model (Armendáriz & Morduch, 2010). Therefore, we argue that MFIs, maximising their social dimensions, should be able to set their interest rate depending on their cost structure and clientele they serve to uphold top social and financial performance. For example, imposing hard caps on interest rates could lead to lower product scope and therefore lower access to credit (Azzalini et al., 2016). Moreover, hard caps could result in negative interest rate margins and as a result MFIs could ask for large upfront fees. Second, hybrids do need to make informed strategic choices when it comes to managing their social performance. We find that MFIs maximising all Schreiner (2002)-dimensions simultaneously comes at the cost of financial sustainability, which is an essential element of running a successful hybrid organisation.

Our research has several important conclusions related to the funding of microfinance institutions. First, donors do not necessarily have to focus their financing efforts towards newer and smaller MFIs. They could directly target relatively larger and/or more mature organisations as they are associated with top joint performance where the institutional goals have already settled in. These MFIs could be more qualified to effectively use the donated funds to further boost their impact by covering the associated additional costs with the received donations. Secondly, a microfinance institution should be cautious with excessive financial risk and bank-like leverage. The debt over equity level of microfinance institutions is much lower than those of traditional banks, indicating that MFIs need to learn how higher debt levels can be harmonised with top joint performance. Moreover, the providers of debt to MFIs should adjust their lending policies and monitor their efforts to stimulate MFIs to be top performers. Additionally, microfinance institutions should carefully screen for the right type of investors before including this type of stakeholder into their MFIs.

Like all research, ours has several limitations that could open up new research tracks. Firstly, we did not fully explore the time dynamics of the data panel because most MFIs appear in our sample for a limited number of years. Therefore, further analysis could try to identify the processes that top performing MFIs go through in harmonising their institutional logics. However, we did find that MFIs have a high likelihood to remain in the same group of social and financial performance for a number of consecutive years[35]. Second, one could improve the number of items used in the feature selection. For example, our microfinance institution variables do not allow us to investigate the influence of new regulations (from the government or management). Our results have shown that political instability is a key performance driver in top performance. However, we can not investigate whether weaker market structures make it easier for clients to set up a business which could increase the repayment rate to MFIs and lead to a higher probability to achieve top joint performance. Finally, researchers could study hybrids in a different industry while utilising the same method to uncover additional important features to reach top performance.

A Appendix

A.1 Self-Organising maps

A self-organising map (SOM) was first introduced by Kohonen in 1981. This paper employs a self-organising map as described in Murtagh and Hernández-Pajares (1995). The self-organising map algorithm consists of two main parts, namely vector quantisation and vector projection, in which the algorithm trains a feed-forward neural network on n-dimensional input data. The output layer is a map with lower dimensionality and a specified number of neurons.

Vector quantisation summarises the n-dimensional data in m groups and each group is represented by its centroid, called a neuron. In the initial phase of the algorithm, data is randomly assigned to different neurons[36]. During each iteration of the algorithm an observation i with data-vector n_i is compared to all the neurons r_k using a distance measure. The neuron r_c with the smallest distance to the input data-vector n_i is called the best matching unit (BMU) and its weights are updated in the direction of the input vector. In other words, the BMU mostly resembles the presented observation and will be updated to become even more similar. A learning rate $l(t)$ determines the magnitude of the adaption of the BMU and a neighbourhood function $h(t)$ defines the range of the influence of the adaption. Meaning that not only the BMU gets updated, but also neurons in the immediate neighbourhood of the winning neuron. Both the learning rate and the neighbourhood function are parameters of a learning function, which updates the values of the neurons:

$$r_k(t) = r_k(t) + l(t)h(t)(n_i(t) - r_k(t)) \tag{2}$$

The learning rate and neighbourhood function are both decreasing functions to ensure that the self-organising map converges.

Afterwards, vector projection reduces the dimensionality of the data by projecting the obtained neurons onto lower dimensional map, a process similar to principal component analysis. Neurons which are in proximity of each other in the high dimensional space should be nearby in the lower dimensional map such that the topology of the input space is kept.

A.2 XGBoost

Equation (3) symbolises a simple representation of the model used for feature selection. $L(\cdot)$ denotes the training loss function and $R(\cdot)$ represents the regularisation term used to prevent over-fitting.

$$\min_{\boldsymbol{\theta}} L(\boldsymbol{\theta}) + R(\boldsymbol{\theta}) \tag{3}$$

The loss function $L(\cdot)$ in step t is given by:

$$\sum_{i=1}^{n} l(y_i, \hat{y}_i^{(t)}) \tag{4}$$

where y_i for $i = 1, \cdots, n$ is the true value of the dependent variable with length n and $\hat{y}_i^{(t)}$ is the predicted value at step t. Moreover, $l(\cdot)$ is a convex loss function. This paper uses a logistic loss function:

$$\sum_{i=1}^{n} \left(y_i \ln(1 + \exp(-\hat{y}_i^{(t)})) + (1 - y_i) \ln(1 + \exp(\hat{y}_i^{(t)})) \right). \tag{5}$$

The algorithm works iteratively and adds a new tree each step, see Equation (6):

$$\begin{aligned}
&\hat{y}_i^{(0)} = 0 \\
&\hat{y}_i^{(1)} = f_1(x_i) = \hat{y}_i^{(0)} + f_1(x_i) \\
&\hat{y}_i^{(2)} = f_1(x_i) + f_2(x_i) = \hat{y}_i^{(1)} + f_2(x_i) \\
&\vdots \\
&\hat{y}_i^{(t)} = \sum_{k=1}^{t} f_k(x_i) = \hat{y}_i^{(t-1)} + f_t(x_i),
\end{aligned} \tag{6}$$

where $f_k(\cdot)$ for $k = 1, \ldots, t$ is a function in the set of all possible regression and classification trees. Each $f_k(\cdot)$ corresponds to an independent tree structure with leaf weights $\boldsymbol{w}$ and T number of leaves. The regularisation function $R(\cdot)$ is given by:

$$\gamma T + \frac{1}{2}\lambda \sum_{j=1}^{T} w_j^2, \tag{7}$$

where w_j is the vector score on the leaves and λ, γ are constants. Moreover, the algorithm uses two additional tools to prevent overfitting, namely shrinkage (J. H. Friedman, 2002) and column sub-sampling (also used in random forest). In summary, in each step t the following minimisation problem needs to be addressed:

$$\sum_{i=1}^{n} \left(y_i \ln(1+\exp(-\hat{y}_i^{(t)})) + (1-y_i)\ln(1+\exp(\hat{y}_i^{(t)})) \right) + \gamma T + \frac{1}{2}\lambda \sum_{j=1}^{T} w_j^2 \tag{8}$$

A.3 Scope of services variable

The scope of services variable is extracted as latent trait out of eight different dummy variables[37]. Six of these variables detail which loan types and thus how many different loan products[38] the MFI offers, as shown in Table A.2. Another dummy variable denotes if the MFI offers savings facilities and the last dummy expresses if the MFI provides plus activities to their clients.

The ‘different loan products variable’ (LP) captures the number of different loan types a MFI offers. This variable has a higher value if the microfinance institution offers more complementary loan types, indicating that clients are more likely to find a loan which suits their needs. To construct this variable, we map the sum of the dummy variables for the loan products to zero-to-one scale, such that higher values correspond to more dummies equal to one.

	Housing	Group	Consumption	Individual	Agriculture	Other type	Plus activities	Saving
0	1277	798	1129	217	821	830	1480	1093
1	916	1395	1064	1976	1372	1363	713	1100

Table A.1: Distribution of the dummy variables used to construct the scope variable

Number of loan products offered	1	2	3	4	5	6
Number of observations	56	313	646	586	430	162

Table A.2: Number of different loan types per observation

Measure	Comparative fit index	Normed fit index	Root mean squared error of approximation	Standardised root mean square residual
Value	1.00	1.00	0.00	0.00

Table A.3: Goodness of Fit of the Scope Measure

A.4 Additional Data Description

	Yearly volatility of return on assets (%)
Count	1508
Std.	6.903
Min	0.000
1st Q.	1.572
Median	3.353
Mean	5.651
3rd Q.	6.586
Max.	49.422

Table A.4: Data description of the volatility of return on assets

Table A.4 shows the volatility of return on assets. It shows that the MFIs in our sample have a quite stable return on assets with a value of 6.586% in the third quantile, indicating that the return on assets does not fluctuate heavily.

	Loan outstanding average	Financial self-sustainability	Return on assets	% of female clients	Scope
Loan outstanding average	1.000	0.081	0.039	-0.206	-0.054
Financial self-sustainability	0.081	1.000	0.576	-0.066	-0.013
Return on assets	0.039	0.576	1.000	0.015	-0.075
% female clients	-0.206	-0.066	0.015	1.000	-0.117
Scope	-0.054	-0.013	-0.075	-0.117	1.000

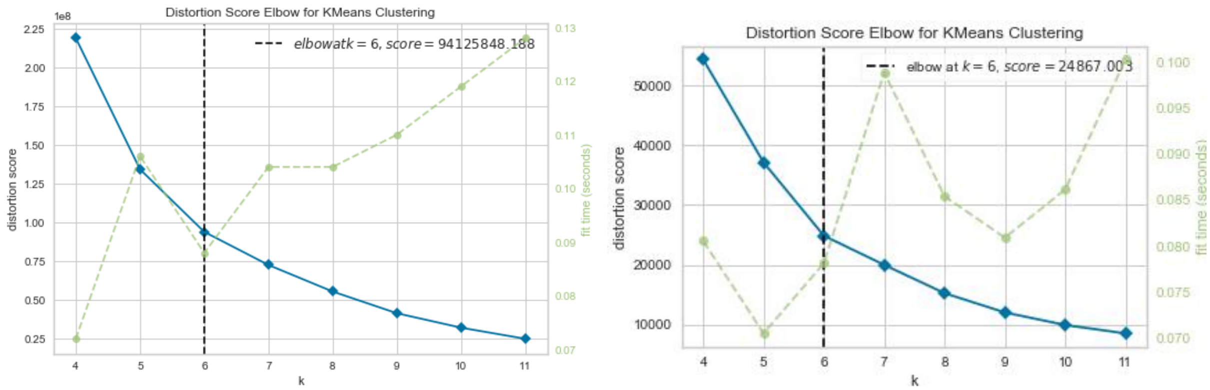
Table A.5: Correlation matrix of the self-organising map variables

	Portfolio yield	Debt/ equity	par30	Loan loss expense rate	ln(assets)	Political Stability	GDP per capita	NBFI	Age
Portfolio yield	1.000	-0.008	-0.087	0.101	-0.205	0.011	-0.077	0.079	-0.163
Debt/equity	-0.008	1.000	0.014	0.009	-0.021	-0.026	-0.020	0.045	0.004
Par30	-0.087	0.014	1.000	0.374	-0.112	-0.039	-0.043	-0.071	0.081
Loan loss expense rate	0.101	0.009	0.374	1.000	-0.044	-0.024	-0.021	0.016	-0.028
ln(assets)	-0.205	-0.021	-0.112	-0.044	1.000	0.033	0.017	0.013	0.315
Political stability	0.011	-0.026	-0.039	-0.024	0.033	1.000	-0.145	0.053	-0.040
GDP per capita	-0.077	-0.020	-0.043	-0.021	0.017	-0.145	1.000	-0.044	0.077
NBFI	0.079	0.045	-0.071	0.016	0.013	0.053	-0.044	1.000	-0.262
Age	-0.163	0.004	0.081	-0.028	0.315	-0.040	0.077	-0.262	1.000

Notes: Par30 is the portfolio at risk over 30 days and NBFI stands for non-bank financial institution, which is a legal type for an MFI.

Table A.6: Correlation matrix of the selected variables of XGboost

A.5 The elbow plot



(a) Portfolio yield is not included

(b) Including portfolio yield

Figure A.1: The elbow plot that determines the number of clusters in K-means clustering using the Industry rating dataset

The elbow plot shows the distortion for each number of clusters where distortion is the average squared distance from the cluster centre to the respective clusters. The optimal number of clusters is selected when the distortion starts decreasing in a linear fashion, in this case when the number of clusters is equal to six for both clustering variables, one where portfolio yield is not included and one where it is (see Figures A.1a and A.1b).

A.6 Additional clustering description

In this section we will describe the different clusters in Figure 2 to provide insight in the results (Dushnitsky et al., 2022). The observations in the brown cluster have the highest scope of services. They provide on average 4-5 different loan products, 62% offer a savings account and 27% offer additional services. Note that this cluster offers one extra loan type compared to the green cluster, less plus activities with respect to it and a comparable number of MFIs between both clusters offers savings accounts. As a result, we argue that the scope of services of the green cluster is still strong.

The Red cluster, the largest cluster, performs weakly negative (-) on the financial and social side. This indicates that many MFIs have a long way to go to be top performing in both dimensions.

From/to	Green	Brown	Red	Blue	Orange/Purple
Green	77.3%	6.1%	16.2%	0.0%	0.3%
Orange/purple	1%	10%	4%	0%	85%

Table A.7: Transition table: movement from the top performing or mission drift cluster to the other clusters between two consecutive years

These MFIs are on average not able to cover their donations and costs with their revenue ($FSS <$ 1), however, they are able to generate a decent return on assets.

The blue cluster is the weakest financial cluster, this cluster is not self-sustainable ($FSS <$ 1) and additionally has a negative return on assets. Notice that the MFIs in this cluster do not offer many different services (second to worst scope of services), however, they do service a lot of women and have the lowest average loan size.

The orange and purple cluster can be labelled as the 'mission drift' clusters in the sense that they serve relatively wealthier clients. Their social performance is extremely poor and their financial performance is very good (FSS bigger than one, positive ROA, less than 50% females and a negative scope on top of the extremely high average loan sizes). Note that these two clusters are not clustered together because the average loan size of the purple cluster is nearly six standard deviations higher than the average loan size of the orange cluster.

In summary, nearly 6 percentage of our sample experiences mission drift and 77 percentage does not excel in one single dimension. This indicates that most MFIs have a long way to go to be top performing.

Now, the question arises how stable the clustering is. Therefore, we investigate the movement between clusters of a top performing and mission drift MFI between two consecutive years. Table A.7 is a transition table which represents these movements. Approximately 77% of the top performing microfinance institutions remain a top performer for another year (move from green cluster to green cluster). This indicates that once a MFI harmonises both underlying goals, it is most likely to remain successful for another year. Hence, the clustering does not change much over time. Notice that most other movements occur to neighbouring clusters (see Figure 2). The movements take place towards the brown, red and orange cluster. In other words, either the top performing MFI shifts focus to the financial side (orange) with higher loan amounts or it expands its scope (brown) at the cost of the other social dimensions (represented by percentage of female clients and average loan outstanding scaled per PPP).

In total, there are 58 distinct microfinance institutions that succeed in combining top social and financial performance in a certain year and 36 of them are top performing over all the years under observation. Meaning that once a MFI manages to institutionalise good performance both financially and socially, the risk of mission drift (Mersland & Strøm, 2010) reduces significantly. Additionally, we investigate the movements of the mission drift cluster (orange or purple cluster). 85% of mission drift MFIs display the mission drift behaviour for another year. This indicates that once mission drift has occurred, it is hard to reverse the process. However, we also observe that 10% of MIFs in the mission drift cluster both lower their average loan size and enlarge their scope (movement towards the brown cluster).

A.7 Geographical location of top performing MFIs

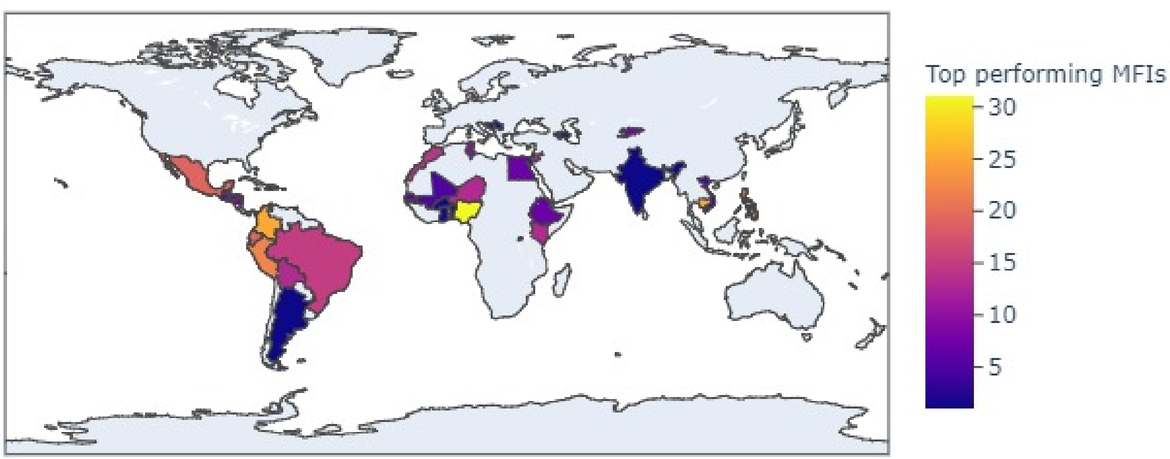


Figure A.2: Geographical location of the top performing MFIs

MFIs are mainly top performing in developing to middle income countries, as shown in Figure A.2. The inhabitants of these countries probably have the highest need for small (affordable) loans and clients in more developed markets have access to a wider spectrum of financial providers. Top performing MFIs primarily reside in three regions: North Africa, Southern Asia and South America. In particular, Nigeria, Cambodia and Colombia harbour the highest number of simultaneously top performing MFIs, respectively 30, 25 and 25 observations.

A.8 Results based on the MIX market dataset

We have reran all our programs on the MIX market dataset and this section will show these results. The final version of the MIX contains 5013 observations. We first analyse the clustering and influential variables when social performance grasps MFIs that offer a wide variety of services to a low income clientele in need. Afterwards, we will show the clusters when we the MFIs also grant their services at low interest rates, proxied by portfolio yield.

A.8.1 Social performance without interest rate charged

The first self-organising map shows that 34.34% of observations are top joint performers (cluster 2). The average values of each cluster are depicted in Table A.8. Additionally, the clustering allows us to pinpoint a mission drift cluster, namely cluster 1. This cluster has excellent financial performance in contrast to its social performance.

	# obs.	ROA	Financial self-sustainability	Loan outstanding average	% of female clients	Scope	Financial	Social
1	1980	0.032	1.185	601.208	0.476	0.004	++	- -
2	1772	0.035	1.161	93.029	0.906	0.030	++	++
3	299	0.103	2.113	771.041	0.669	-0.140	++	-
4	559	-0.66	0.641	235.837	0.670	-0.099	-	-
5	327	0.011	1.126	8357.362	0.407	0.139	++	-
6	76	-0.408	0.312	128.251	0.734	-0.207	- -	+

Table A.8: Average values per cluster of the self-organising map for the MIX market dataset

Figure A.3 shows the results of XGboost when using the MIX market dataset. First observe that almost all of the most influential variables overlap with the most influential variables of

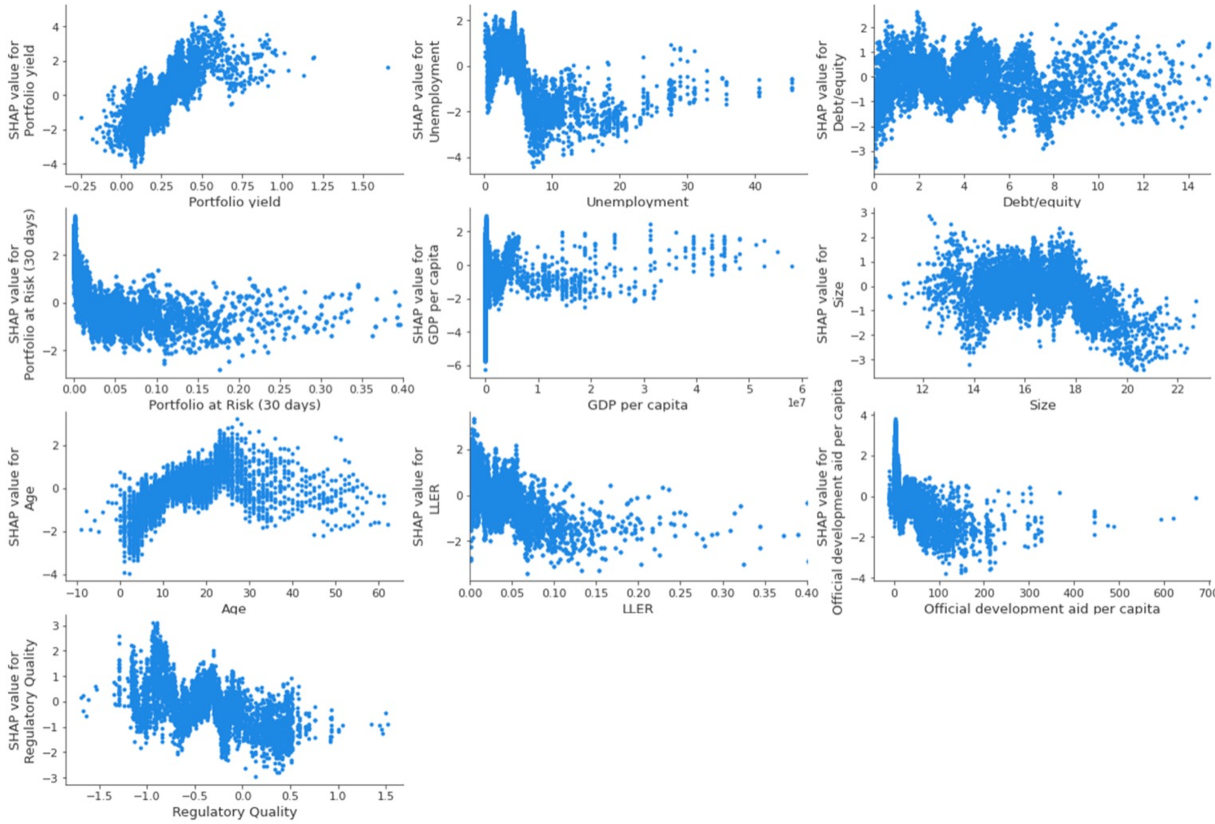


Figure A.3: Results of XGboost based on the MIX market dataset

the industry rating dataset. The only variable that is switched here is the legal type “non-bank financial institution” for the official development aid per capita and the unemployment rate. Note that in this case, eleven variables in the model are preferred over nine since it results in a higher accuracy. The final accuracy of this model is 80.98%, which is slightly lower than the accuracy of the model for the rating dataset, however, it is still very high. Moreover, we find similar results in the patterns of the most influential variables on top joint performance.

In short, we first observe that higher portfolio yields associate with top social and financial performance. Second, a top performing microfinance institution limits its credit and financial risk since lower debt over equity levels, portfolio at risk and loan loss expense rate correlate with top joint performance. Third, countries with low GDP per capita positively link with top joint performance. Fourth, we can observe that the result for age shows a U-shaped relationship with top joint performance, indicating that a microfinance institution experiences a learning effect and later on mission drift. Fifth, countries with lower unemployment levels associate with top joint performance. Lastly, we observe that countries with lower levels of regulatory quality positively correspond with top joint performance.

A.8.2 Social performance including interest rate charged

	# obs.	ROA	Financial self-sustainability	Loan outstanding average	% female clients	Scope	Portfolio yield	Financial	Social
1	397	0.01	1.12	7461.06	0.44	0.07	0.15	+	0
2	2039	0.02	1.11	293.29	0.65	0.27	0.19	+	+
3	427	0.08	1.88	697.03	0.69	0.15	0.19	++	+
4	383	-0.16	0.52	237.24	0.60	-0.15	0.26	- -	- -
5	1191	0.03	1.16	376.40	0.68	-0.56	0.23	++	-
6	576	0.06	1.19	110.04	0.84	0.13	0.50	++	+

Table A.9: Average values per cluster of the self-organising map for the MIX market dataset

In this section, we expand social performance with one extra variable, namely the cost of taking a loan, proxied by the portfolio yield. We observe in Table A.9 that the top performing cluster vanishes, now none of the clusters show excellent social and financial performance in all underlying variables. However, we have two clusters, namely cluster 3 and 6, which excel in multiple social and in all financial dimensions. Microfinance institutions in cluster 3 offer many different types of products, i.e., it has a high scope, ask rather low interest rates and serves more females than the sample median. We observe that this cluster serves relatively wealthier clients (the average loan size is higher) and as such might be able to ask lower interest rates for its services. On the other hand, MFIs in cluster 6 score excellent on all dimensions except for portfolio yield. This cluster services relatively poorer clients in need with a variety of services while keeping strong financial performance. However, servicing these clients comes at the cost of higher interest rates to assure good financial performance. Hence, both these results indicate that combining low interest rates, good social outreach, offering a high scope of products, issuing small loans and maintaining good financial performance is not reconcilable. A microfinance institution should be able to stay afloat and combining all these features will not generate enough income to cover all the associated costs.

Notes

[1]The former is referred to as scaling-up whereas the latter is referred to as scaling-down towards a full-fledged social enterprise.

[2]Poverty-focus denotes the poverty level of the clients, the social outreach indicates that the MFI reaches people in need for financial services and scope of services denotes the number of different services the microfinance institution offers.

[3]Top performing in the sense that they have excellent financial performance while providing a wide variety of products to a poor clientele in need for financial services.

[4]In other words the trade-off situation occurs.

[5]The synergy situation

[6]Schreiner (2002) framed different dimensions of social performance for microfinance institutions, ranging from the poverty level of clients, to social outreach, diversity of delivered products and the cost of microfinance services. Schreiner (2002) has suggested length of outreach and value to clients as additional dimensions, however, these indicators are difficult to measure (Mersland & Strøm, 2008).

[7]Note that in the literature poverty-focus is often quantified by average loan size per client per GNI (McIntosh et al., 2005; Mersland & Strøm, 2010; Mosley & Hulme, 1998; Kar, 2012). In this paper, we prefer scaling with PPP-adjustments rather then GNI-adjustments because this is more aligned with the actual size of a loan, i.e., less influenced by the overall wealth of the country. For example, oil-producing countries often have an unreasonable high GNI per capita.

[8]For example, poorer and/or remote clients are costlier to serve.

[9]The ratio of revenue over expenses adjusted for subsidies or donations (Cull et al., 2009).

[10]Donations enter in the denominator of FSS.

[11]The construction of this variable is detailed in the appendix in Section A.3.

[12]Unsupervised learning algorithms

[13]For example in investigating wellbeing in households (Lucchini & Assi, 2012).

[14]More technical details can be found in the appendix.

[15]The technical details regarding XGBoost can be found in the appendix.

[16]CERSEM `https://cersem.uia.no/`

[17]Microfinanza, Microrate, M-CRIL, Planet rating and Crisil.

[18]We have re-run our whole methodology on the MIX market dataset in the appendix and the results are comparable.

[19]The scope variable uses 8 variables, 6 variables construct the self-organising map, 11 variables detail the country-specific environment, 6 other variables detail the MFI-specific characteristics and 9 dummies describe the legal and market type of the MFI.

[20]Note that we do not remove the outliers because we cluster observations in groups based on their performance. The extreme cases will end up together in an ‘extreme’ cluster. For example, we could detect a group with high average loan sizes,

every microfinance institution with a high loan size (winsorised or not) will end up in this group.

[21]Table A.1 provides an overview of the distribution of the underlying dummy variables which form the base of the scope of services variable. Table A.2 clarifies the number of loan types per observation.

[22]The denominator is calculated as a yearly rolling average of the total assets.

[23]Note that an MFI can have a positive ROA while $FSS < 1$, because FSS is adjusted for donations.

[24]See Table A.5 in the appendix.

[25]A non bank financial institution (NBFI) is owned by shareholders and allowed only to market a limited number of banking services.

[26]Note that, in countries where MFIs operate, most people work in the informal sector and as such are not incorporated in the unemployment statistics.

[27]The optimal number of clusters is determined by the elbow plot in Figure A.1a.

[28]One individual indicator is deemed '+' if its value is above the sample median (and the sample average for average loan size because the distribution is extremely right skewed) and '-' otherwise. The total social performance receives a '+' if the majority of individual components receives a plus sign and negative otherwise. The overall negative performance obtains a '-' sign if both individual components got a negative sign but in general their performance is considered good, which means that $FSS > 1$ and $ROA > 0$. Lastly, the total negative performance receives a positive sign if one of the two underlying indicators received a plus sign and the other indicator is still considered good.

[29]As determined in Figure A.1b.

[30]Figure 3g also shows that all other legal types (NBFI=0), including NGO and cooperative, have a positive effect on joint top performance. As such, this result is in line with Prasenjit and Ambika (2018) and Gupta and Mirchandani (2020) who state that NGOs have excellent social performance and might even be better suited to uphold the double bottom-line.

[31]Note that annual interest rates of 40% are equal to 2.86% per month and 0.649% per week. Moreover, an annualised interest rate of 40% is close to the sample average of 36.9%.

[32]The annualised interest rates of the top performing cluster are on average 6.5 percentage points higher than the observations not in this cluster. This result also explains why we could not find a top performing cluster with low interest rates.

[33]If you pay a daily rate of 1% but are able to generate revenues of 10% per day, you would be glad to take the 360% interest rate per year loan.

[34]On average 42.5%

[35]See appendix Section A.6

[36]A well-known example of vector quantisation is k-means clustering.

[37]Further research could initialise the weights of each dummy variable with the share of the different services in the total income of MFIs.

[38]Group, agricultural, individual, consumption, housing or other type of loan. The number of times each type is offered can be consulted in Table A.1.

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