Explaining Failures of Microfinance Institutions

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Abstract

We empirically study the determinants of failures of microfinance institutions based on the CAMELS rating components and microfinance-specific measures by applying probit regression techniques. Our findings confirm the capital adequacy (C), the asset quality (A), the management capability (M), the earnings (E), and the sensitivity to market risk (S) as explaining factors of failures of microfinance institutions. Regarding microfinance-specific effects, there is a positive influence of the percentage of female borrowers on the likelihood of failure. Moreover, we find evidence that regulation, the presence of donations, and the rapid growth of an MFI affect the probability of failure.

Keywords: microfinance, MFI failure, CAMELS, regulation, gender

JEL: G21, G23, G32, L26

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1. Introduction

The myth that microfinance institutions (MFIs) operate successfully even without proper management structures has persisted for a long time (Armendáriz and Morduch, 2010, p. 347). However, Armendáriz and Morduch (2010) argue that efficient management structures are of great importance regarding the success or failure of an MFI. Their view is supported by a more frequent observation of MFI failures after the financial crisis of 2008/2009 due to poor portfolio quality or weak management (see e.g. Rozas, 2009, 2011).

MFIs differ from standard banks. They mainly operate in developing countries granting loans to poor entrepreneurs, often without any collateral. Bruton et al. (2013) stress the importance of entrepreneurship as a tool for poverty reduction. However, sufficient amounts of funding required to operate their businesses are unavailable for many microentrepreneurs. Contrary to commercial banks, MFIs are willing to meet the financing needs of microenterprises (see Khavul et al., 2013, p. 31).

Many MFIs focus on female clients. Moreover, in microfinance, various organizational types can be found. Not all MFIs are organized as banks, but as non-bank financial institutions (NBFIs), credit unions, or non-governmental organizations (NGOs), to name the most important possibilities. Another important difference between standard banks and MFIs is that not every MFI is allowed to collect deposits. Furthermore, as many MFIs pursue a social mission they often receive donations. As a consequence, insights on bank failures from traditional banking literature may not be applicable to MFIs. Deepening the knowledge on failures of MFIs is therefore crucial for regulators, investors, depositors, microentrepreneurs, and other stakeholders of these institutions. This article is the first to

investigate the failures of MFIs systematically.

For our analysis, we use annual balance sheet and income statement data on 1,797 MFIs in 117 countries from 1995 until 2011, which we replenish with information regarding financial distress derived from extensive online investigations. To detect failed MFIs, we examine breaks in the data history. We identify documented failures, e.g., MFIs that have been closed by a legal authority due to bankruptcy, defaulted on a loan, undergone a restructuring process, or were forced to merge with another MFI due to financial distress.

In banking literature, there is a vast body of evidence that can be found on bank failures. Many investigations focus on US banks and use the CAMEL(S) rating components as exogenous variables. CAMELS is an acronym for capital adequacy, asset quality, management capability, earnings, liquidity, and sensitivity to market risk. While older studies focus on the five CAMEL rating components, more recent analyses (e.g., Kerstein and Kozberg, 2013) often employ the sensitivity to market risk as an additional element as well. For example, Thomson (1991) examines predictors of bank failures for the period from 1982 until 1989, basing his proxy variables on the elements of the CAMEL rating. Using balance sheet and income statement data, he conducts a logit regression for subsamples regarding the time to failure and detects several predictors for bank failure. For example, the return on assets of a bank serves as a predictor for failure. Banks with a lower return on assets are more likely to fail. The definition for bank failure varies across different studies. In addition to bank failures, Wheelock and Wilson (2000) investigate acquisition hazards using a hazard model in the period from 1984 until 1993. Furthermore, they use two definitions of failure. The first definition regards the closure of a bank by the regulatory authority and the second

definition expands the first definition by including banks with a ratio of total equity less goodwill to total assets of less than or equal to two percent. The findings of Wheelock and Wilson (2000) also show a significant negative influence of the return on assets on failure. Jin et al. (2011) explore the accounting and the audit quality as predictors for bank failures, which they detect by examining a list published online by the Federal Deposit Insurance Corporation and find a negative relationship between the reputation of the auditor and failure.

There are also studies analysing bank distress outside the United States. For example, Arena (2008) explores bank failures in nine East Asian countries for the period from 1995 until 1999 and six Latin American countries for the period from 1992 until 1996 using a cross-sectional multivariate logit model. His definition of failure again differs from the previously mentioned studies. Männasoo and Mayes (2009) investigate 19 Eastern European transmission economies for the period from 1995 until 2004 by applying a survival model. Moreover, they provide a brief summary of further studies on bank failures (e.g., Whalen, 1991; González-Hermosillo et al., 1997) including the various definitions for bank failures or distress. The findings of the studies described by Männasoo and Mayes (2009) are similar. The capital asset ratio, the earnings variables, and the liquidity ratio appear to be negatively related to failure and there is a positive relationship between the measures for asset risk and failure.

In microfinance literature, to our knowledge Rozas (2009) and Rozas (2011) are the only studies to describe MFI failures in a case study style. In both studies, the author reveals several reasons for the failing of MFIs, such as fraud by the managers or a growth that is too rapid. Furthermore, there is some literature on aspects related to the failure of MFIs, e.g. the management of MFIs and the fi-

nancial performance (see, e.g., Hudon, 2010), the governance (see, e.g., Mersland and Strøm, 2009), or MFI ratings (see, e.g., Beisland and Mersland, 2012).

Other previous research in the field of microfinance investigates several effects of different measures on performance indicators, e.g., financial revenue, sustainability, outreach or the portfolio quality of MFIs. D'Espallier et al. (2011) examine whether MFIs with a focus on female borrowers exhibit a better repayment performance. They analyse a global data set on rating data of 350 MFIs via panel regressions. Their findings demonstrate that MFIs with a larger share of female borrowers exhibit a better asset quality in terms of portfolio at risk, loan write-off rate, and provision expense rate. Tchakoute-Tchuigoua (2010) investigates performance differences between MFIs with a different legal status. His results indicate that the portfolio at risk of private companies is significantly lower than it is for cooperatives and NGOs. Furthermore, Assefa et al. (2013) examine the effect of competition, measured by a self-constructed Lerner index, on performance indicators. Their results show a positive relationship of competition with the portfolio at risk and the write-off ratio. Baquero et al. (2012), who examine the influence of competition, observe contradictory results on micro loan interest rates and the portfolio at risk. They reveal that the portfolio at risk of for-profit MFIs is lower in more competitive markets. Dorfleitner et al. (2013) examine determinants of microcredit interest rates and find a positive relationship between the loan loss rate and the lending rate charged by MFIs from their borrowers.

The contribution of this article is twofold. First, we investigate whether the findings from the standard banking literature (mainly the CAMELS components) can be confirmed when explaining failures of MFIs. Our results suggest that several bank-specific variables identified to determine failures in the traditional bank-

ing literature also explain failures of MFIs, e.g., capital adequacy and portfolio quality. Second, due to the difference between traditional banks and MFIs, we also analyse the microfinance-specific determinants of MFI failures. For example, we find that a higher fraction of female borrowers is associated with a higher probability of failure.

The remainder of this article is structured as follows. Section 2 describes the data, hypotheses, and methodology. Section 3 presents the results. It contains detailed descriptive statistics, several probit models, robustness checks, and discusses the results by comparing our findings with previous research on traditional banks. Finally, Section 4 concludes and provides suggestions for further research.

2. Data and methodology

2.1. Data

Data sources. Our data set combines three data sources. Data concerning MFIs were obtained from the Microfinance Information Exchange (MIX) through the web-based information platform MIX Market, which makes a variety of self-reported indicators from MFIs openly available. However, these data lack crucial measures such as donations received by MFIs. Therefore, we include data on MFI income statements that were also obtained from MIX. As we additionally wish to control for the influence of country-specific effects on MFI failures, we add macroeconomic indicators obtained from the World Bank. All three data sources consist of panel data on an annual basis for the period between 1995 and 2011. Due to data inconsistencies, we carefully clean the data obtained from the MIX Market from unrealistic values, for example, a portfolio at risk, share of female borrowers, average loan size, asset value or liquid assets smaller than zero,

replacing them with missing values.

Identifying failures. Additionally, information on MFI failures was collected through extensive online research. As of January 2013, 964 out of 2,370 MFIs ceased reporting to MIX Market at some point in time. The change in this reporting behaviour could either be attributed to a merger or a failure of the MFI or it stopped reporting for other reasons, e.g., lack of personnel or time. We analysed the reasons for the break in the reporting history of every MFI that stopped reporting to MIX Market. We classify these MFIs as failed, non-failed, and unsolved with respect to a reference year and in accordance with the two failure definitions shown in Section 2.2. The reference year is the point in time with a failure indication, i.e., the breaks in the reporting history. The classification algorithm is shown in the Appendix. We exclude the 264 MFIs whose situation remains unsolved from the analysis, when we analyse the strict definition of failure. Section 2.2 provides detailed descriptions of both definitions of failure.

Cross-sectional indicators. Although panel data are available, the implementation of panel regression techniques is not suitable due to the limited number of failures. Therefore, we construct cross-sectional indicators for all variables of interest by aggregating the MFI's data over the last three years – but over a minimum of 2 years – available before the reference year, by using the average value. We regard institutions reporting an average loan size larger than 15,000 USD as not being focused on microfinance. To avoid distortion, we exclude the corresponding observations from the data set.

2.2. Definitions of failure

The strict definition (FAILURE1), which we employ for our main analyses, comprises documented failures. Therefore, we investigated extensively, mainly via online research, whether the reason for the discontinued data history of an MFI was a merger or a failure. MFIs are categorized as having failed if they were actually liquidated by a legal authority due to bankruptcy, defaulted on a loan or were merged with other MFIs after financial distress. Financial distress is indicated by a capital asset ratio of less than or equal to two percent. Merged MFIs with a capital asset ratio of more than two percent are not regarded as having failed according to our strict definition. Additionally, we found nine MFIs that underwent restructuring and continued reporting afterwards. These MFIs also fall into the category of failed MFIs. The category of non-failed includes those MFIs that are no longer engaged in microfinance after ceasing to report to MIX or those MFIs who represent temporary microfinance projects that were expectedly terminated.

As a robustness check, we explore an additional extended definition of failure (FAILURE2) following Wheelock and Wilson (2000). According to this definition, an MFI is regarded as non-failed, if it reports a capital asset ratio of more than two percent in the last year with data available in the data history on MIX Market between 1995 and 2011. Consequently, an MFI is categorized as having failed if the MFI has a capital asset ratio of less than or equal to two percent in the last year it reported upon. In these cases, we anticipate the time of failure to be the point in time at which the capital asset ratio first falls below the mentioned threshold and does not recover afterward. If the capital asset ratio time series of an MFI consists only of values below the threshold, we cannot determine the year

of the anticipated failure and consequently exclude this MFI from the sample. The extended definition additionally includes all MFIs that failed according to the strict definition.

Since both failure definitions require information on the capital asset ratio, which is also an explanatory variable (see below), we generally apply the following principle: For each MFI we decide whether a failure or a non-failure has been observed at some point in time. To explain these events in the regression analyses, we strictly use variables from at least one year before the observed failure or non-failure. While, due to this procedure, we lose some observations because of inadequately short time series before the anticipated or actual failure event, its benefit is that the regression analyses do not suffer from self-inflicted endogeneity.

Dependent on the failure definition applied, the data used to calculate the cross sectional indicators also vary for some MFIs. Hence, we distinguish between the two data sets FAILURE1 data and FAILURE2 data referring to the failure definition that is used to determine failures in the data. Table 1 presents the number of MFIs per country and the number of failed MFIs according to the strict and extended definition of failure. Note that the distribution of the observations over the countries is very imbalanced.

2.3. Explanatory variables and hypotheses

As the aim of this paper is to investigate whether the CAMELS components explain failures of MFIs and to determine additional microfinance-specific factors, we follow the traditional bank failure literature (e.g., Thomson, 1991; Arena, 2008; Männasoo and Mayes, 2009) and additionally include microfinance-specific variables to derive the possible determinants of failure.

As a proxy for *capital adequacy*, we use the capital asset ratio. We would

Table 1: Number of MFIs per country and number of failures according to the strict (FAILURE1) and extended (FAILURE2) definition.

	No. MFIs					No. MFIs			
	FAILURE1		FAILURE2			FAILURE1		FAILURE2	
Country	total	failed	total	failed	Country	total	failed	total	failed
Afghanistan	17	4	17	6	Macedonia	4	0	4	0
Albania	6	0	6	0	Madagascar	13	0	12	0
Angola	2	0	2	0	Malawi	6	0	7	0
Argentina	18	0	17	0	Malaysia	1	0	1	0
Armenia	12	0	13	0	Mali	16	1	17	2
Azerbaijan	24	0	22	0	Mexico	66	1	64	1
Bangladesh	72	0	61	2	Moldova	4	0	4	0
Belarus	–	–	1	0	Mongolia	6	0	7	0
Belize	1	0	1	0	Montenegro	4	0	3	0
Benin	25	0	18	2	Morocco	11	1	11	1
Bhutan	1	0	1	0	Mozambique	8	0	9	0
Bolivia	25	0	25	0	Myanmar (Burma)	1	0	1	0
Bosnia and Herzegovina	16	1	15	1	Namibia	2	0	2	0
Brazil	30	0	25	1	Nepal	38	0	40	0
Bulgaria	20	0	25	0	Nicaragua	32	5	32	6
Burkina Faso	13	0	9	0	Niger	8	0	10	0
Burundi	5	0	4	0	Nigeria	50	4	46	4
Cambodia	17	0	16	0	Pakistan	30	0	30	4
Cameroon	21	0	20	1	Palestine	8	0	8	0
Central African Republic	1	0	1	0	Panama	4	0	3	0
Chad	2	0	2	0	Papua New Guinea	2	0	2	0
Chile	5	0	5	0	Paraguay	7	0	7	0
China, People's Republic of	34	0	30	3	Peru	65	0	67	1
Colombia	37	0	34	0	Philippines	98	1	96	2
Congo, Democratic Republic of the	11	0	14	1	Poland	4	0	3	0
Congo, Republic of the	4	0	4	0	Romania	6	0	6	0
Costa Rica	15	0	15	0	Russia	29	0	59	3
Cote d'Ivoire (Ivory Coast)	17	0	9	0	Rwanda	21	0	7	0
Croatia	2	0	2	0	Saint Lucia	1	0	–	–
Dominican Republic	13	1	13	1	Samoa	1	0	1	1
East Timor	3	0	3	0	Senegal	21	0	20	3
Ecuador	57	0	55	1	Serbia	4	0	4	0
Egypt	14	0	14	1	Sierra Leone	9	0	10	0
El Salvador	16	0	17	1	Slovakia	1	0	1	0
Ethiopia	21	0	18	0	South Africa	10	0	8	0
Fiji	1	0	–	–	South Sudan	4	0	3	0
Gabon	1	0	1	0	Sri Lanka	23	0	23	0
Gambia, The	2	0	2	0	Sudan	2	0	2	0
Georgia	13	0	12	0	Suriname	1	0	–	–
Ghana	52	0	44	1	Swaziland	1	0	1	0
Grenada	1	0	–	–	Syria	3	0	3	1
Guatemala	22	0	22	0	Tajikistan	36	0	32	0
Guinea	7	0	7	1	Tanzania	15	1	15	1
Guinea-Bissau	4	0	2	1	Thailand	3	0	2	0
Haiti	7	0	6	0	Togo	13	1	12	3
Honduras	23	0	23	0	Tonga	1	0	1	0
Hungary	1	0	1	0	Trinidad and Tobago	2	0	2	0
India	146	12	146	20	Tunisia	1	0	1	0
Indonesia	31	1	52	1	Turkey	2	0	2	0
Iraq	12	0	12	0	Uganda	23	1	23	1
Jamaica	3	0	3	0	Ukraine	3	0	3	0
Jordan	8	0	8	0	Uruguay	2	1	2	1
Kazakhstan	22	1	30	1	Uzbekistan	18	0	30	0
Kenya	27	2	25	2	Vanuatu	1	0	–	–
Kosovo	11	0	10	0	Venezuela	2	0	2	0
Kyrgyzstan	24	0	33	0	Vietnam	23	0	19	0
Laos	3	0	3	0	Yemen	9	0	8	2
Lebanon	5	0	5	0	Zambia	7	0	6	0
Liberia	3	0	2	0	Zimbabwe	5	0	5	0
					Total	1797	39	1782	85

expect MFIs with a higher capital asset ratio to be less likely to fail. The portfolio at risk (30 days), the portfolio at risk (90 days), the loan loss rate, and the write-off ratio are commonly used measures for the portfolio quality in microfinance (see, e.g. Cull et al., 2007; Tchakoute-Tchuigoua, 2010; D'Espallier et al., 2011; Ahlin et al., 2011; Assefa et al., 2013) and serve as different proxies for *asset quality*. There should be a positive relationship between the proxies for (bad) asset quality and the probability of failure. The ratio of borrowers per staff member is a proxy for *management capability*. This measure is generally not employed in studies on traditional bank failures. However, Armendáriz and Morduch (2010) emphasise that the motivation of staff members is an important factor for the management capability of an MFI. We suggest a negative relationship between borrowers per staff member and the probability of failure because MFIs with a higher number of borrowers per staff member are expected to operate more efficiently.

We consider the return on assets, the profit margin, and the net operating income as measures for the *earnings* of an MFI. MFIs with higher earnings are assumed to be less likely to fail. We employ the liquid assets as a proxy for *liquidity* and expect the failure probability to be lower for MFIs with a higher ratio of liquid assets. In line with Kerstein and Kozberg (2013), who investigate interest bearing deposits to total assets as a proxy for the *sensitivity to market risk*, we analyse the effect of deposits to total assets on the probability of failure. Contrary to Kerstein and Kozberg (2013), we expect a lower probability of failure with higher levels of deposits in the context of microfinance. Not all MFIs collect deposits. Only if an MFI meets certain criteria concerning its type or regulation is it allowed to take deposits from its clients. However, deposits are an inexpensive source of funding compared to debt from international investors. The dependence on international

capital markets is lower for MFIs that collect deposits. Therefore, the interest rate risk decreases for MFIs with higher levels of deposits. Moreover, these MFIs may also face a lower currency risk.

The fact that not all MFIs are able to offer deposits marks one of several differences between MFIs and standard banks. Accounting for these differences, we additionally examine microfinance-specific factors. We assume the percentage of female borrowers, donations, regulation, and growth effects to have an influence on the failure probability of an MFI. The discussion about gender effects is a well-known topic in microfinance. According to D'Espallier et al. (2011), MFIs with a higher fraction of female borrowers display a better repayment performance. However, Hermes et al. (2011) argue that MFIs focusing on women operate less efficiently. We expect the share of female borrowers to have a positive impact on the failure probability of an MFI after controlling for the overall asset quality.

Another important difference to standard banking is that many MFIs receive donations. On the one hand, donations increase the equity of MFIs and reduce the pressure on an MFI to operate efficiently. Hence, this effect may cause donations to be positively associated with the event of failure. On the other hand, there could also be a negative relationship between donations and the probability of failure if donors determined certain requirements regarding the operations of an MFI. Furthermore, if an MFI is accompanied by a donor, it is very likely that the donor will help the MFI in times of financial distress. To observe the relationship between donations and the failure probability we include either a donations dummy or the relative donations divided by average assets, respectively.

Contrary to traditional banks, not all MFIs are subject to some form of regulation. However, regulation may reduce the likelihood of failure. Hence, we expect

a negative relationship between the regulation dummy and the probability of failure. Moreover, Rozas (2011) mentions fast, uncontrolled growth of MFIs as being a reason for some of the MFI failures that he studies. To examine whether such an effect holds true after controlling for other effects, we proxy the growth of an MFI with the average growth rate of the number of an MFI's borrowers (NBdev).

In summary, our empirical analyses focus on the following five hypotheses.

Hypothesis 1 (H1). *The CAMELS components affect the probability of failure.*

Hypothesis 2 (H2). *There is a positive relationship between the percentage of female borrowers and the probability of failure.*

Hypothesis 3 (H3). *Donations have an influence on the likelihood of failure.*

Hypothesis 4 (H4). *Regulated MFIs are less likely to fail.*

Hypothesis 5 (H5). *The growth rate of an MFI in terms of number of borrowers is positively related to the probability of failure.*

Further explanatory variables include several MFI-specific and macroeconomic control variables. The average assets are included to control for the size of the MFI. Furthermore, we include a dummy variable indicating whether the respective MFI operates for-profit. We also include a dummy variable for the region Latin America and the Caribbean. The MFI types in our data sample are BANK, NGO, NBFI, credit union (CU), and OTHER[1]. We control for the type of MFI by including a dummy variable for the type NGO.

[1]The category OTHER includes rural banks and MFIs that do not provide information on the type on MIX Market.

We also include macroeconomic control variables in our analysis, for example, the GDP per capita, the GDP growth, a measure for the competition, and a proxy for the agricultural production in a country (CropI). This measure considers, for example, crop shortfalls due to natural disasters. To account for the overall poverty level in a country, we include the poverty rate. We follow Cull et al. (2007) and employ the average loan size as a proxy for the poverty level of the borrowers of an MFI. Additionally, we include the Gini index to capture the distribution of income in the country where the MFI is located. All variables are defined in detail in Table 2.

2.4. Limitations of the data set

Several previous empirical studies mention selection bias issues related to MIX Market data (see, e.g., Bauchet and Morduch, 2010; Assefa et al., 2013). Indeed, it is not unlikely that our data set comprises larger and more mature MFIs because reporting to MIX Market is voluntary for MFIs. Hence, a great number of MFIs possibly is neither able nor willing to contribute to MIX Market, which could be the case for small and/or young MFIs in particular. However, as our analyses focus on MFIs that intend to attract investors and as the MFIs providing information not only aim to enhance transparency[2] but also look for new sources of financing, we argue that the MFIs reporting to MIX are most likely representative of those MFIs which seek financing.

Additional concerns may arise due to the fact that smaller and less mature MFIs, which we cannot capture in our data set, might tend to fail more often in

[2]While transparency is of special importance to investors, other stakeholders, for example depositors or microentrepreneurs, may possibly rely on other factors enhancing the confidence in a certain MFI.

Table 2: Definition of variables.

Variable	Description	
CAP	Capital asset ratio	Total equity divided by total assets. Source: MIX Market.
PAR	Portfolio at risk	Measures the unpaid principal of loans on which installments have been 30 days (or 90 days) past due and is based on the total outstanding credit balance. Source: MIX Market.
LLR	Loan loss rate	Value of loans written off less value of recovered loans divided by average gross loan portfolio. Source: MIX Market.
WOR	Write off ratio	Obtained by dividing the value of non-collectable loans by the average gross loan portfolio. Source: MIX Market.
Borrowers per staff member	Borrowers per staff member	Number of active borrowers divided by number of personnel. Source: MIX Market.
ROA	Return on assets	Net operating income less taxes divided by average assets. Source: MIX Market.
Profit margin	Profit margin	Net operating income divided by financial revenue. Source: MIX Market.
NOI	Net operating income	Net operating income divided by average total assets. Source: Derived from MIX income statements.
Liquid assets	Liquid assets	Non-earning liquid assets divided by average total assets. Source: Derived from MIX Market.
Deposits/Total Assets	Deposits/Total Assets	Deposits in USD divided by the total assets. Source: Derived from MIX Market.
WB	Women ratio	Share of MFI borrowers that are female. Source: MIX Market.
Donations/Average Assets	Donations	Donations in USD divided by the average total assets. Source: Derived from MIX income statements.
Donations (dummy)	Donations	Indicates whether an MFI receives donations. MFIs with no information are included in the reference category. Dummy variable. Source: Derived from MIX income statements.
Regulated (dummy)	Regulation	Indicates whether an MFI is subject to the supervision of a regulatory authority. Dummy variable. Source: MIX Market.
NB	Number of borrowers	Number of active borrowers. Source: MIX Market.
NBdev	NB growth rate	NBdev is the average discrete rate of increase of an MFI's number of active borrowers. Source: Derived from MIX Market.
Assets	Average total assets	Average value of total assets at the start and end of the reporting period in USD. Source: Derived from MIX Market.
AVLS	Average loan size	Average gross loan portfolio in USD divided by the number of borrowers of the institution. Source: MIX Market.
For-profit (dummy)	Profit status	Indicates if an MFI operates for profit or not (non-profit). The non-profit category includes MFIs with no information. Dummy variables. Source: MIX Market.
Type	Type of institution	Legal status of the MFI: Credit union (CU), Bank (BANK), non-bank financial institution (NBFI), non-governmental organization (NGO), other (OTHER). Dummy variables. Source: MIX Market.
Region	Region	The geographical regions are Latin America and the Caribbean (LAC), the Middle East and North Africa (MENA), Africa (AFRICA), South Asia (SA), Eastern Europe and Central Asia (EECA), and East Asia and the Pacific Area (EAP). Source: MIX Market.
GDPpc	Gross domestic income per capita	USD value of gross domestic income of the country, in which the MFI mainly operates, divided by its midyear population. Source: World Bank data.
GDP growth	GDP growth	Annual growth of GDP per capita in percent. Source: World Bank data.
CropI	Crop Index	The crop production index accounts for the agricultural production, with the exception of fodder crops, for each year and country. Base period: 2004–2006. Source: World Bank data.
Gini index	Gini index	Measure for income inequality. Source: World Bank data.
Comp	Competition	Reciprocal of the summed squares of the MFI market shares. The market shares are calculated as the number active borrowers of an MFI divided by the number of active borrowers in each country based on the MIX data.
Poverty rate	Poverty rate	Headcount below national poverty line in the country the MFI operates divided by the total population. Source: World Bank data.
Shares	Value of shares traded	Total value of stocks traded divided by GDP. Source: World Bank data.
Credit	Domestic credit provi- ded by financial sector	Domestic credit provided by financial sector divided by GDP. Source: World Bank data.
OE	Operating expenses	Operating expense divided by average assets. Employed as instrument in probit regressions with endogenous regressors. Source: MIX Market.
Lending interest rate	Lending interest rate	Country's lending interest rate. Employed as instrument in probit regressions with endogenous regressors. Source: World Bank data.

comparison to their peers represented at MIX Market. However, because of the lack of information, we are not able to consider these MFIs in our investigation. Again, as we are only interested in the MFIs that wish to attract potential investors, the MFIs not reporting to MIX Market are not in the scope of our investigation. Furthermore, for our regression analyses it is not necessary to identify the correct proportion of failed MFIs among all MFIs. The analyses solely require the failed MFIs of our sample to be representative for failed MFIs in general. The data show no indication contrary to this assumption. Moreover, we exclude unsolved cases regarding the FAILURE1 data set to avoid misspecification of failures. To conclude, although a certain sample selection bias exists, we are confident of the representativeness of our data set concerning the intended analyses.

2.5. Methodology

The dependent variable is a binary indicator for MFI failures. We estimate regression models with the following probit specification:

$$probit\left\{P(y_i = 1|X)\right\} = \beta X_i + \varepsilon_i, \tag{1}$$

where X is a vector of explanatory variables concerning MFI i and $\varepsilon_i \sim N(0, \sigma_e^2)$ is an individual residual. We apply Eicker–Huber–White heteroskedastic-consistent standard errors in all regressions.

Probit models are frequently used to determine the factors influencing failures of traditional banks (e.g., Cole and Gunther, 1998; Reynaud, 2010; Kerstein and Kozberg, 2013). Other regression techniques comprise logit models (e.g., Thomson, 1991; Arena, 2008; Cole and White, 2012; Jin et al., 2011), the

linear probability model (e.g., Poghosyan and Čihak, 2011), and survival models[3] (e.g., Wheelock and Wilson, 2000; Arena, 2008; Auvray and Brossard, 2012).

There are several MFIs that do not report all variables required for the analyses. Because failures are already rare events in our data sample, we follow D'Espallier et al. (2011) and impute metric variables with their means to prevent the loss of these observations.

3. Results

3.1. Descriptive analysis

Table 3 shows the frequencies of failed and non-failed MFIs according to the strict (column 2–4) and extended (column 5–7) definition of failure for the categorical variables. The FAILURE1 data set includes 39 failed and 1758 non-failed MFIs while the FAILURE2 data set consists of 85 failed and 1697 non-failed MFIs. Although it is possible that our data set may be biased regarding the size due to the usage of MIX Market information, as mentioned in Section 2.4, the majority of MFIs operates on a non-profit basis in both failure samples. Over 40% of the MFIs receive donations.

Table 4 presents the descriptive statistics for the metric variables of the full sample (Panel A) and the sample of failed MFIs (Panel B) according to the strict definition. Table 5 exhibits the full sample (Panel C) and the sample of failed MFIs (Panel D) according to our extended definition.

[3] We are not able to estimate survival models because we cannot determine the failure date.

Table 3: Frequencies for categorical variables based on the unimputed data sets for the strict (FAILURE1) and extended (FAILURE2) definition of failure. The variables are defined in Table 2.

	FAILURE1			**FAILURE2**		
	No	Yes	Total	No	Yes	Total
Type						
Bank	157	4	161	145	4	149
Credit Union	295	5	300	312	15	327
NBFI	498	17	515	483	20	503
NGO	646	11	657	588	43	631
Other	162	2	164	169	3	172
Region						
Africa	440	10	450	374	23	397
East Asia and the Pacific	218	2	220	220	7	227
Eastern Europe and Central Asia	270	2	272	323	5	328
Latin America and The Caribbean	447	8	455	427	13	440
Middle East and North Africa	72	1	73	67	5	72
South Asia	311	16	327	286	32	318
Regulated						
No	654	18	672	652	41	693
Yes	1,026	21	1,047	979	42	1,021
No information	78	0	78	66	2	68
Operational self-sufficiency						
No	513	22	535	448	49	497
Yes	1,136	17	1,153	1,155	33	1,188
No information	109	0	109	94	3	97
Profit status						
Non-profit	991	21	1,012	964	64	1,028
Profit	666	15	681	645	17	662
No information	101	3	104	88	4	92
Deposits						
No	600	14	614	561	27	588
Yes	990	16	1,006	933	31	964
No information	168	9	177	203	27	230
Donations						
No	861	24	885	836	39	875
Yes	733	14	747	712	42	754
No information	164	1	165	149	4	153
Total	1,758	39	1,797	1,697	85	1,782

Table 4: Descriptive statistics for metric variables based on the unimputed data set for the strict definition of failure (FAILURE1). The variables are defined in Table 2.

				Quantiles				
Variable	n	Mean	S.D.	Min	0.25	Mdn	0.75	Max
Panel A: Full sample	1797							
CAP	1758	0.314	0.291	−3.639	0.137	0.243	0.457	1.000
WOR	1542	0.022	0.048	−0.010	0.000	0.006	0.023	0.577
LLR	1620	0.018	0.046	−0.323	0.000	0.003	0.018	0.563
PAR30	1572	0.081	0.126	0.000	0.017	0.046	0.094	2.350
PAR90	1401	0.055	0.085	0.000	0.009	0.029	0.063	0.933
OE	1641	0.195	0.181	0.000	0.095	0.145	0.236	2.782
Borrowers per staff member	1724	134.723	259.006	0.000	56.000	101.000	157.167	8191.667
ROA	1642	−0.009	0.154	−2.930	−0.016	0.015	0.043	0.577
Profit margin	1662	−0.098	0.753	−9.656	−0.100	0.086	0.194	1.423
NOI	1666	−0.008	0.152	−2.930	−0.018	0.018	0.048	0.485
Deposits/Total Assets	1590	0.244	0.288	0.000	0.000	0.107	0.466	0.973
Liquid assets	1517	0.170	0.131	0.000	0.080	0.136	0.222	0.846
NB (in thousands)	1747	56.982	361.502	0.000	1.634	6.579	23.036	7498.742
NBdev	1514	0.415	3.823	−0.966	−0.022	0.109	0.320	142.000
Assets (mn USD)	1767	36.337	167.286	0.000	0.900	3.276	13.738	3553.838
AVLS	1735	1133.627	1816.088	1.000	156.500	440.333	1260.500	14825.000
Donations/Average Assets	1644	0.037	0.149	−0.035	0.000	0.000	0.010	3.472
WB	1537	0.637	0.267	0.000	0.424	0.623	0.897	1.000
DQI	1797	0.176	0.192	0.000	0.000	0.118	0.314	0.941
GDPpc	1784	2715.224	2753.615	121.014	762.747	1251.168	3865.162	17142.119
Comp	1793	6.660	4.403	1.000	3.442	5.161	10.754	21.839
CropI	1782	109.752	13.199	62.140	102.335	109.130	116.360	215.285
Poverty rate	1061	32.652	12.927	2.900	24.900	32.367	39.800	80.700
Domestic credit provided by financial sector	1706	45.410	30.387	−19.142	22.695	42.006	60.829	184.570
Value of shares traded	1289	20.300	32.806	0.002	1.102	4.386	20.398	157.419
Gini index	1106	42.238	8.693	26.975	33.380	42.980	48.713	67.400
Lending interest rate	1449	15.441	9.514	5.396	10.833	13.783	17.973	203.961
GDP per capita growth (annual %)	1784	3.370	2.854	−9.410	1.303	3.263	4.987	21.722

				Quantiles				
Variable	n	Mean	S.D.	Min	0.25	Mdn	0.75	Max
Panel B: Failed MFIs	39							
CAP	39	0.144	0.180	−0.206	0.058	0.120	0.245	0.713
WOR	36	0.032	0.051	0.000	0.000	0.014	0.035	0.243
LLR	38	0.031	0.049	−0.007	0.000	0.014	0.034	0.243
PAR30	37	0.124	0.121	0.000	0.033	0.080	0.175	0.438
PAR90	29	0.112	0.131	0.000	0.009	0.047	0.185	0.466
OE	39	0.199	0.158	0.019	0.089	0.134	0.290	0.666
Borrowers per staff member	36	167.370	137.090	16.500	72.500	117.667	236.833	466.333
ROA	39	−0.050	0.135	−0.509	−0.128	−0.015	0.038	0.177
Profit margin	37	−0.289	0.710	−2.489	−0.601	−0.065	0.124	1.024
NOI	37	−0.050	0.136	−0.450	−0.097	−0.014	0.042	0.185
Deposits/Total Assets	29	0.116	0.208	0.000	0.000	0.020	0.071	0.694
Liquid assets	30	0.207	0.157	0.007	0.091	0.177	0.302	0.692
NB (in thousands)	38	177.950	447.208	0.521	5.364	12.842	84.175	2233.332
NBdev	35	0.569	1.331	−0.490	−0.051	0.170	0.696	6.683
Assets (mn USD)	39	52.879	99.307	0.042	0.992	6.011	39.053	397.776
AVLS	38	784.781	1181.023	36.000	146.000	227.500	1073.000	4761.333
Donations/Average Assets	38	0.040	0.085	0.000	0.000	0.000	0.007	0.376
WB	36	0.734	0.262	0.130	0.590	0.724	1.000	1.000
DQI	39	0.154	0.156	0.000	0.000	0.118	0.294	0.471
GDPpc	39	1467.031	1722.690	255.298	447.961	1119.172	1176.748	9402.997
Comp	39	7.313	4.417	1.000	2.920	5.467	11.711	15.667
CropI	39	104.064	11.279	67.415	99.850	105.120	114.287	116.360
Poverty rate	25	35.437	10.165	9.000	29.800	36.800	39.000	61.700
Domestic credit provided by financial sector	39	46.704	27.684	2.402	17.268	60.016	70.341	96.037
Value of shares traded	26	38.301	34.986	0.002	6.266	26.923	76.168	85.057
Gini index	18	38.031	8.080	27.820	29.740	38.285	46.160	50.550
Lending interest rate	35	15.936	12.127	7.600	11.278	13.511	16.440	83.468
GDP per capita growth (annual %)	39	4.057	3.080	−5.900	1.947	3.932	5.729	8.834

Table 5: Descriptive statistics for metric variables based on the unimputed data set for the extended definition of failure (FAILURE2). The variables are defined in Table 2.

				Quantiles				
Variable	n	Mean	S.D.	Min	0.25	Mdn	0.75	Max
Panel C: Full sample	1782							
CAP	1770	0.335	0.259	−0.565	0.144	0.255	0.478	1.000
WOR	1506	0.020	0.041	−0.019	0.000	0.005	0.022	0.556
LLR	1598	0.020	0.172	−0.079	0.000	0.003	0.017	6.695
PAR30	1538	0.072	0.127	0.000	0.013	0.042	0.087	3.506
PAR90	1341	0.048	0.072	0.000	0.009	0.027	0.059	0.980
OE	1628	0.198	0.204	0.000	0.094	0.144	0.235	2.782
Borrowers per staff member	1707	127.609	227.763	0.000	53.500	95.000	154.333	8191.667
ROA	1629	−0.005	0.171	−2.930	−0.011	0.017	0.046	0.577
Profit margin	1652	−0.064	0.695	−7.744	−0.066	0.094	0.206	1.049
NOI	1656	−0.000	0.150	−2.930	−0.012	0.019	0.051	0.559
Deposits/Total Assets	1548	0.251	0.293	0.000	0.000	0.113	0.492	0.999
Liquid assets	1476	0.166	0.132	0.000	0.076	0.132	0.220	0.846
NB (in thousands)	1729	51.455	330.800	0.000	1.386	5.968	21.009	7498.742
NBdev	1493	0.573	5.068	−0.789	−0.012	0.112	0.326	142.000
Assets (mn USD)	1772	35.147	165.318	0.000	0.803	3.026	12.768	3553.838
AVLS	1714	1176.367	1840.928	1.000	164.667	475.333	1308.667	14486.000
Donations/Average Assets	1640	0.046	0.209	−0.035	0.000	0.000	0.011	3.999
WB	1499	0.632	0.268	0.000	0.423	0.620	0.886	1.000
DQI	1782	0.177	0.193	0.000	0.000	0.118	0.314	0.941
GDPpc	1770	2757.898	2784.989	98.821	762.747	1328.934	3979.047	14202.633
Comp	1779	6.655	4.417	1.000	3.440	5.170	10.834	22.496
CropI	1769	108.595	13.082	67.000	101.493	107.913	115.785	215.285
Poverty rate	1054	32.307	13.665	2.900	22.950	31.510	39.800	76.400
Domestic credit provided by financial sector	1704	43.973	29.379	−20.813	22.617	41.905	60.016	183.328
Value of shares traded	1316	20.645	32.365	0.000	1.201	5.608	22.958	179.438
Gini index	1134	41.805	8.553	26.975	33.710	42.760	48.713	63.140
Lending interest rate	1449	15.477	9.254	5.310	10.833	13.737	17.973	188.104
GDP per capita growth (annual %)	1770	3.516	3.064	−14.314	1.503	3.435	5.364	27.261

				Quantiles				
Variable	n	Mean	S.D.	Min	0.25	Mdn	0.75	Max
Panel D: Failed MFIs	85							
CAP	85	0.156	0.195	−0.206	0.049	0.094	0.225	1.000
WOR	67	0.034	0.060	0.000	0.000	0.013	0.037	0.361
LLR	72	0.032	0.058	−0.007	0.000	0.011	0.033	0.361
PAR30	72	0.158	0.417	0.000	0.019	0.070	0.182	3.506
PAR90	53	0.097	0.118	0.000	0.008	0.047	0.150	0.466
OE	73	0.214	0.179	0.019	0.109	0.149	0.240	0.850
Borrowers per staff member	78	132.346	108.515	0.000	70.667	99.917	163.000	466.333
ROA	73	−0.069	0.160	−0.793	−0.116	−0.028	0.026	0.177
Profit margin	80	−0.363	0.796	−4.265	−0.582	−0.172	0.114	1.024
NOI	80	−0.067	0.151	−0.685	−0.098	−0.028	0.024	0.185
Deposits/Total Assets	57	0.143	0.237	0.000	0.000	0.017	0.180	0.822
Liquid assets	57	0.188	0.149	0.007	0.068	0.150	0.273	0.692
NB (in thousands)	81	93.411	316.103	0.000	2.054	8.520	25.608	2233.332
NBdev	75	0.568	1.679	−0.490	−0.051	0.128	0.665	12.167
Assets (mn USD)	85	27.945	71.425	0.000	0.660	2.363	17.748	397.776
AVLS	80	633.754	1052.417	19.000	127.750	213.417	536.167	5514.333
Donations/Average Assets	81	0.052	0.115	0.000	0.000	0.000	0.062	0.609
WB	75	0.704	0.269	0.102	0.498	0.695	0.993	1.000
DQI	85	0.224	0.191	0.000	0.000	0.235	0.353	0.647
GDPpc	85	1567.164	1812.760	166.996	535.108	1076.789	1189.717	9402.997
Comp	85	6.798	4.555	1.000	3.178	5.059	11.711	21.839
CropI	85	103.630	10.404	67.415	99.350	102.703	114.287	120.920
Poverty rate	49	36.434	12.698	9.000	29.800	36.800	40.000	71.300
Domestic credit provided by financial sector	85	44.635	32.260	−1.934	18.600	45.490	66.285	145.080
Value of shares traded	53	45.282	43.529	0.002	6.651	42.823	76.168	179.438
Gini index	42	38.575	7.735	27.820	32.140	38.805	44.430	55.890
Lending interest rate	68	15.051	10.550	5.310	11.278	12.908	16.017	83.468
GDP per capita growth (annual %)	85	3.988	2.992	−5.900	1.627	3.932	5.729	9.185

Concerning the CAMELS-rating components, the capital adequacy of the average failed MFI appears to be worse than the capital adequacy of the average MFI in the respective full sample. Furthermore, the proxies for the (bad) asset quality (PAR30, PAR90, LLR, and WOR) appear to be higher for the average failed MFI (Panel B and D) than for the average MFI in Panel A and C. The proxies for the earnings exhibit negative values for ROA, profit margin, and NOI. However, the earnings measures are lower for the MFIs in Panels B and D compared to the full sample (Panel A and C). The measure for liquidity is higher in the failed MFIs samples than in the respective full samples. This result is consistent with the descriptive findings of Koetter et al. (2007), who analyse the determinants of distressed and non-distressed bank mergers. In their sample, distressed acquired banks show the highest liquidity. In contrast, the average MFI in the full sample exhibits a larger share of deposits relative to total assets than the average failed MFI. Among the MFI-specific variables, the most outstanding differences include the average number of borrowers, the fraction of female borrowers, and the average outstanding balance.

Table 6 presents Bravais–Pearson correlation coefficients for the metric exogenous variables based on the imputed data sets. To avoid multicollinearity, we use solely the portfolio at risk (30 days) and the loan loss rate to proxy (bad) asset quality, and the return on assets to measure earnings in the regression analyses.

Table 6: Bravais–Pearson correlation coefficients for metric exogenous variables based on the imputed data sets. The symbols *, **, and *** express significance at the 10%, 5%, and 1% level, respectively. The variables are defined in Table 2.

FAILURE1 data set (N = 1797)

		1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.
1.	CAP	1.00											
2.	WOR	0.01	1.00										
3.	LLR	0.07***	0.93***	1.00									
4.	PAR30	−0.04	0.26***	0.21***	1.00								
5.	PAR90	−0.05**	0.24***	0.19***	0.73***	1.00							
6.	Borrowers per staff member	−0.02	0.17***	0.20***	0.01	0.03	1.00						
7.	ROA	0.12***	−0.18***	−0.17***	−0.10***	−0.09***	0.02	1.00					
8.	Profit margin	0.09***	−0.21***	−0.20***	−0.11***	−0.09***	0.04	0.65***	1.00				
9.	NOI	0.17***	−0.19***	−0.17***	−0.10***	−0.09***	0.02	0.94***	0.69***	1.00			
10.	Liquid assets	−0.04*	0.11***	0.09***	0.13***	0.15***	−0.01	−0.12***	−0.15***	−0.13***	1.00		
11.	Deposits/Total Assets	−0.33***	−0.08***	−0.09***	0.08***	0.08***	−0.06**	0.05**	0.05**	0.05**	0.25***	1.00	
12.	WB	−0.06**	−0.05**	−0.04	−0.14***	−0.08***	0.13***	−0.03	−0.01	−0.03	−0.01	−0.17***	1.00
13.	Donations/Average Assets	0.10***	0.04	0.04*	−0.02	−0.02	−0.03	−0.65***	−0.45***	−0.65***	0.07***	−0.10***	0.01
14.	NBdev	0.04*	−0.02	−0.03	−0.03	−0.04	−0.02	−0.03	−0.08***	−0.04	0.01	−0.03	−0.02
15.	logaAssets	−0.18***	0.02	0.04	−0.07***	−0.05**	0.08***	0.16***	0.20***	0.17***	0.05**	0.18***	−0.13***
16.	log(AVLS)	−0.01	0.01	−0.01	0.02	−0.01	−0.24***	0.08***	0.10***	0.08***	−0.10***	0.17***	−0.56***
17.	GDPpc	0.11***	0.07***	0.07***	−0.03	−0.05**	−0.04*	−0.05**	0.02	−0.05**	−0.20***	−0.15***	−0.14***
18.	GDP per capita growth (annual %)	0.01	−0.15***	−0.14***	−0.09***	−0.05**	0.05**	0.06***	0.06***	0.07***	−0.01	−0.03	0.05**
19.	CropI	−0.03	−0.01	−0.02	−0.06***	−0.06**	0.03	0.04*	0.01	0.04*	−0.05**	0.02	0.09***
20.	Gini index	0.02	0.10***	0.09***	0.06**	0.02	0.02	−0.03	0.01	−0.04	−0.10***	0.09***	−0.07***
21.	Comp	−0.16***	−0.07***	−0.05**	−0.06**	−0.01	0.04*	0.10***	0.11***	0.10***	−0.03	0.10***	0.19***
22.	Value of shares traded	0.01	−0.02	−0.02	−0.04	−0.03	0.09***	−0.01	−0.01	−0.01	−0.07***	−0.18***	0.16***
23.	Poverty rate	0.00	0.08***	0.08***	0.01	−0.02	−0.05*	−0.02	−0.07***	−0.02	0.01	−0.02	0.02
24.	Domestic credit provided by financial sector	0.04*	0.01	0.01	−0.03	0.01	0.07***	−0.04	0.06**	−0.03	−0.14***	−0.22***	0.18***

		13.	14.	15.	16.	17.	18.	19.	20.	21.	22.	23.	24.
13.	Donations/Average Assets	1.00											
14.	NBdev	0.01	1.00										
15.	logaAssets	−0.19***	−0.04*	1.00									
16.	log(AVLS)	−0.12***	0.03	0.36***	1.00								
17.	GDPpc	0.01	−0.01	0.13***	0.43***	1.00							
18.	GDP per capita growth (annual %)	−0.00	0.06***	−0.10***	−0.16***	−0.20***	1.00						
19.	CropI	−0.05**	−0.00	0.18***	−0.05**	−0.12***	0.12***	1.00					
20.	Gini index	−0.01	−0.01	0.08***	0.16***	0.28***	−0.22***	−0.08***	1.00				
21.	Comp	−0.10***	−0.03	0.11***	−0.14***	−0.15***	0.09***	0.07***	0.11***	1.00			
22.	Value of shares traded	−0.02	0.13***	−0.02	−0.15***	0.01	0.35***	0.12***	−0.05*	0.03	1.00		
23.	Poverty rate	0.01	0.00	−0.05**	−0.06**	−0.10***	−0.21***	−0.11***	0.25***	0.05**	−0.06***	1.00	
24.	Domestic credit provided by financial sector	−0.05**	0.07***	0.02	−0.10***	0.17***	0.18***	−0.02	0.04	−0.02	0.57***	−0.21***	1.00

FAILURE2 data set (N = 1782)

		1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.
1.	CAP	1.00											
2.	WOR	0.04*	1.00										
3.	LLR	0.04	0.22***	1.00									
4.	PAR30	−0.03	0.20***	0.04*	1.00								
5.	PAR90	−0.03	0.22***	0.05**	0.59***	1.00							
6.	Borrowers per staff member	−0.03	0.25***	0.05**	0.04*	0.08***	1.00						
7.	ROA	0.04*	−0.20***	−0.02	−0.07***	−0.06**	0.02	1.00					
8.	Profit margin	−0.01	−0.22***	−0.04	−0.08***	−0.07***	0.04*	0.60***	1.00				
9.	NOI	0.10***	−0.22***	−0.03	−0.08***	−0.07***	0.02	0.83***	0.71***	1.00			
10.	Liquid assets	−0.01	0.10***	0.02	0.09***	0.10***	−0.01	−0.09***	−0.14***	−0.11***	1.00		
11.	Deposits/Total Assets	−0.40***	−0.12***	−0.03	0.06**	0.06**	−0.06***	0.04*	0.06***	0.05**	0.21***	1.00	
12.	WB	−0.03	−0.01	0.02	−0.08***	−0.02	0.14***	−0.04*	−0.04*	−0.03	−0.01	−0.17***	1.00
13.	Donations/Average Assets	0.12***	0.02	−0.00	−0.03	−0.03	−0.03	−0.74***	−0.39***	−0.54***	0.04*	−0.08***	0.04
14.	NBdev	0.02	−0.03	−0.01	−0.03	−0.03	−0.03	−0.02	−0.05**	−0.04*	0.01	−0.04	−0.03
15.	logaAssets	−0.26***	0.06***	−0.02	−0.02	0.01	0.11***	0.12***	0.19***	0.12***	0.07***	0.15***	−0.11***
16.	log(AVLS)	−0.04*	−0.02	0.00	−0.01	−0.00	−0.23***	0.09***	0.12***	0.09***	−0.09***	0.18***	−0.55***
17.	GDPpc	0.09***	0.10***	0.00	−0.03	−0.05**	−0.03	−0.03	0.00	−0.05*	−0.21***	−0.08***	−0.12***
18.	GDP per capita growth (annual %)	0.01	−0.14***	−0.01	−0.10***	−0.07***	0.02	0.03	0.06**	0.06**	−0.05**	−0.04	0.02
19.	CropI	−0.06**	−0.03	−0.02	−0.02	−0.02	0.07***	0.06***	0.03	0.05*	−0.03	−0.00	0.12***
20.	Gini index	−0.00	0.14***	0.01	0.04*	0.00	0.04*	−0.01	−0.01	−0.04	−0.10***	0.06**	−0.01
21.	Comp	−0.23***	−0.05**	−0.03	−0.03	0.04*	0.05**	0.05**	0.09***	0.07***	−0.01	0.10***	0.21***
22.	Value of shares traded	0.03	−0.04	−0.02	−0.02	−0.02	0.09***	−0.02	−0.02	−0.01	−0.07***	−0.15***	0.17***
23.	Poverty rate	0.04*	0.10***	0.02	0.02	0.00	−0.02	−0.04*	−0.09***	−0.04	−0.01	−0.06***	0.04*
24.	Domestic credit provided by financial sector	0.08***	0.01	−0.02	−0.03	0.01	0.11***	−0.00	0.05*	0.01	−0.11***	−0.21***	0.18***

		13.	14.	15.	16.	17.	18.	19.	20.	21.	22.	23.	24.
13.	Donations/Average Assets	1.00											
14.	NBdev	0.01	1.00										
15.	logaAssets	−0.20***	−0.07***	1.00									
16.	log(AVLS)	−0.14***	0.01	0.35***	1.00								
17.	GDPpc	−0.02	−0.02	0.15***	0.43***	1.00							
18.	GDP per capita growth (annual %)	0.03	0.08***	−0.12***	−0.09***	−0.14***	1.00						
19.	CropI	−0.10***	−0.01	0.24***	−0.05**	−0.09***	0.06**	1.00					
20.	Gini index	−0.05**	−0.03	0.12***	0.11***	0.27***	−0.25***	−0.04	1.00				
21.	Comp	−0.06***	−0.04*	0.10***	−0.16***	−0.13***	0.05**	0.10***	0.16***	1.00			
22.	Value of shares traded	−0.01	0.08***	−0.01	−0.15***	0.02	0.31***	0.13***	−0.07***	0.05**	1.00		
23.	Poverty rate	0.04	0.01	−0.06***	−0.09***	−0.11***	−0.23***	−0.07***	0.29***	0.05**	−0.05**	1.00	
24.	Domestic credit provided by financial sector	−0.05**	0.03	0.06***	−0.10***	0.13***	0.12***	0.02	0.03	0.02	0.54***	−0.20***	1.00

3.2. Regression analysis

Table 7 shows the results of the estimated probit models for the strict definition of MFI failure based on the imputed data set. Several studies on bank failures solely employ the CAMEL(S)-rating components in their regression analyses (e.g., Cole and Gunther, 1998; Oshinsky and Olin, 2006). Hence, model specification (I) includes the CAMELS components with neither MFI-specific variables nor control variables. To account for the differences between MFIs and traditional banks, model specification (II) contains the microfinance-specific variables related to our hypotheses H2–H5 derived in Section 2.3. Again, no further explanatory variables are involved. Instead of the dummy variable indicating whether the MFI receives donations, model specification (III) includes the relative donations. Other studies on bank failure employ a measure for the size as additional control variable (e.g., Kerstein and Kozberg, 2013). In line with this literature, model specification (IV) controls for the size by containing the average total assets. Following Thomson (1991), Männasoo and Mayes (2009), and Poghosyan and Čihak (2011), who employ additional control variables, model specification (V) accounts for all control variables described in Section 2.3. All model specifications are estimated employing Eicker–Huber–White heteroskedastic-consistent errors.

All coefficients of the CAMELS components, except for the liquidity, show the expected sign. Our results show a significant negative relationship between the proxy for capital adequacy, i.e. CAP, and FAILURE1 across all model specifications. The coefficient of the first proxy for the (bad) asset quality, PAR30, is positive and significant in model (I) to (V). While the coefficient of the second proxy for (bad) asset quality shows the expected positive sign it is only significant in model specifications (II), (III), and (V). The proxy for management ca-

Table 7: Coefficients of the probit models. The dependent variable is the FAILURE1 dummy. The regression is performed using Eicker–Huber–White heteroskedastic-consistent errors. Standard errors are in parentheses. The symbols *, **, and *** express significance at the 10%, 5%, and 1% level, respectively. The variables are defined in Table 2.

	(I)	(II)	(III)	(IV)	(V)
CAMELS components					
CAP	−0.808***	−0.804***	−0.786***	−0.811***	−0.816***
	(0.220)	(0.218)	(0.218)	(0.216)	(0.233)
PAR30	0.641*	0.680*	0.729**	0.852**	0.858**
	(0.346)	(0.355)	(0.365)	(0.371)	(0.400)
LLR	1.464	1.909*	1.735*	1.634	2.054*
	(1.045)	(1.024)	(1.035)	(1.071)	(1.230)
Borrowers per staff member (in thousand)	−0.0122	−0.0749	−0.0586	−0.124	−0.200*
	(0.119)	(0.107)	(0.107)	(0.108)	(0.111)
ROA	−0.0784	−0.177	−0.202	−0.436	−0.821**
	(0.367)	(0.328)	(0.566)	(0.299)	(0.406)
Liquid assets	0.930*	0.891*	0.830	0.889	0.394
	(0.538)	(0.538)	(0.537)	(0.543)	(0.666)
Deposits/Total Assets	−0.996***	−0.933***	−0.915***	−0.940***	−1.185***
	(0.315)	(0.313)	(0.317)	(0.309)	(0.366)
MFI-specific variables					
WB		0.593*	0.560*	0.686**	0.862**
		(0.310)	(0.306)	(0.308)	(0.413)
Donations (dummy)		−0.217		−0.204	−0.276*
		(0.144)		(0.145)	(0.163)
Donations/Average Assets			−0.220		
			(0.552)		
Regulated		0.0281	0.0519	−0.0415	−0.276*
		(0.134)	(0.139)	(0.135)	(0.165)
NBdev		0.00625	0.00710	0.00772	0.00769
		(0.00583)	(0.00565)	(0.00557)	(0.00577)
Control variables					
logaAssets				0.0979**	0.190***
				(0.0399)	(0.0447)
log(AVLS)					−0.0768
					(0.0976)
For-profit					−0.142
					(0.204)
TYPE_NGO					−0.561**
					(0.221)
Region LAC					0.359
					(0.311)
GDPpc (in thousand USD)					−0.168**
					(0.0685)
GDP per capita growth (annual %)					0.0687**
					(0.0286)
CropI					−0.0352***
					(0.00591)
Gini index					−0.00749
					(0.0118)
Poverty rate					0.00764
					(0.00795)
Comp					−0.00355
					(0.0162)
Constant	−1.873***	−2.224***	−2.293***	−3.769***	−0.483
	(0.133)	(0.277)	(0.276)	(0.674)	(1.088)
Observations	1797	1797	1797	1797	1797
Failures	39	39	39	39	39
Pseudo-R^2	0.081	0.096	0.090	0.115	0.240
AIC	361.6	363.9	365.9	358.6	331.8

pability, borrowers per staff member, appears to have a significant influence on FAILURE1, in the model specification including all control variables. Hence, the higher the management capability, the lower the probability of failure.[4] The mea-

[4]Note that a high value for the deposits to total assets indicates a low sensitivity to market risk.

sure for the earnings is negative across all model specifications. It is significant when control variables additional to size are included. The proxy for liquidity does not show the expected negative sign. However, liquidity does not seem to have a significant effect on the probability of failure in model specifications (III)–(V). Concerning the measure for the sensitivity to market risk, all model specifications indicate a significant negative relationship between the sensitivity and FAILURE1. Regarding our hypotheses, we observe evidence supporting H1 concerning the capital adequacy (C), the asset quality (A), the management capability (M), the earnings (E), and the sensitivity to market risk (S).

Concerning the microfinance-specific variables, the fraction of female borrowers, WB, is positive and significant across all model specifications. Therefore, an MFI is more likely to fail if it has a higher ratio of female borrowers. This is consistent with our expectations in Section 2.3. Hence, our results provide evidence in favour of H2. Although there is evidence that MFIs with a focus on female microfinance clients show better repayment rates (see D'Espallier et al., 2011), our finding regarding H2 is consistent with the conclusions of previous studies in the field of microfinance. For example, as already mentioned in Section 2.3, Hermes et al. (2011) reveal a negative effect of the focus on female borrowers on the efficiency of an MFI. The coefficients of the donations dummy and the relative donations are negative in all model specifications. The finding regarding the donations dummy is significant in model (V) when all control variables are included. Therefore, there is evidence to support H3. The coefficient of the dummy indicating regulation is significant in model specification (V). Thus, our main results supply evidence approving H4. Finally, the rapid growth proxy NBdev shows a positive coefficient in all specifications, although this finding is not significant.

Hence, we find no evidence in favour of H5 regarding our main model (V).

3.3. Robustness analysis

To assess the robustness of our results, we conduct further regressions. First, we investigate the extended definition of failure. Model specifications (R.I)–(R.V) in Table 8 represent the respective results corresponding to the models in Table 7 with FAILURE2 as dependent variable. All model specifications are estimated employing Eicker–Huber–White heteroskedastic-consistent errors.

The results regarding the proxies for the CAMELS components are similar to the model specifications with FAILURE1. The only differences arise regarding the asset quality and the management capability. While we are able to detect a positive relationship between PAR30 and the probability of failure, the coefficient of LLR is insignificant. However, it shows the expected sign. Similarly, our results show no significant effect of the management capability on the likelihood of failure in the FAILURE2 sample. In terms of the MFI-specific variables, none of the coefficients is significant, except for the positive coefficient of WB in model (R.III). Moreover, there are differences regarding the signs of several coefficients, for example, NBdev.

Table 9 displays additional robustness checks regarding the FAILURE1 data set. Model specification (R.VI) corresponds to model (V) but is estimated employing country-clustered standard errors. Furthermore, we add several control variables to model specification (V) that measure the development of the financial system in a country (models R.VII and R.VIII), namely the value of shares traded and the domestic credit provided by the financial sector divided by GDP. Moreover, we conduct several subsample regressions. While model specification (R.IX) regards a subsample without NGOs, model (R.X) solely explores MFIs that do not

Table 8: Coefficients of the probit models. The dependent variable is the FAILURE2 dummy. The regression is performed using Eicker–Huber–White heteroskedastic-consistent errors. Standard errors are in parentheses. The symbols *, **, and *** express significance at the 10%, 5%, and 1% level, respectively. The variables are defined in Table 2.

	(R.I)	(R.II)	(R.III)	(R.IV)	(R.V)
CAMELS components					
CAP	−2.163***	−2.151***	−2.118***	−2.188***	−2.027***
	(0.443)	(0.446)	(0.454)	(0.438)	(0.426)
PAR30	1.704***	1.800***	1.699***	1.802***	1.945***
	(0.477)	(0.478)	(0.483)	(0.476)	(0.491)
LLR	0.197	0.197	0.180	0.184	0.156
	(0.129)	(0.128)	(0.128)	(0.128)	(0.121)
Borrowers per staff member (in thousand)	−0.132	−0.192	−0.194	−0.140	−0.227
	(0.111)	(0.156)	(0.141)	(0.115)	(0.215)
ROA	−0.459*	−0.403*	−1.003**	−0.331	−0.454**
	(0.242)	(0.242)	(0.494)	(0.242)	(0.210)
Liquid assets	0.666	0.592	0.599	0.633	0.294
	(0.420)	(0.429)	(0.425)	(0.431)	(0.480)
Deposits/Total Assets	−1.182***	−1.076***	−1.072***	−1.094***	−1.081***
	(0.218)	(0.233)	(0.233)	(0.234)	(0.287)
MFI-specific variables					
WB		0.369	0.388*	0.337	0.239
		(0.227)	(0.229)	(0.229)	(0.304)
Donations (dummy)		0.0634		0.0657	−0.0852
		(0.117)		(0.117)	(0.131)
Donations/Average Assets			−0.659		
			(0.445)		
Regulated		−0.0581	−0.0707	−0.0349	−0.0760
		(0.119)	(0.118)	(0.116)	(0.147)
NBdev		−0.00256	−0.00367	−0.00443	−0.00669
		(0.00815)	(0.00821)	(0.00795)	(0.00797)
Control variables					
logaAssets				−0.0345	0.0635*
				(0.0284)	(0.0339)
log(AVLS)					−0.0719
					(0.0706)
For-profit					−0.297*
					(0.158)
TYPE_NGO					0.0693
					(0.165)
Region LAC					−0.199
					(0.228)
GDPpc (in thousand USD)					−0.0662*
					(0.0384)
GDP per capita growth (annual %)					0.0380**
					(0.0184)
CropI					−0.0239***
					(0.00517)
Gini index					0.00276
					(0.0100)
Poverty rate					0.0111*
					(0.00601)
Comp					−0.00919
					(0.0142)
Constant	−1.104***	−1.358***	−1.322***	−0.831*	0.517
	(0.133)	(0.219)	(0.215)	(0.492)	(0.860)
Observations	1782	1782	1782	1782	1782
Failures	85	85	85	85	85
Pseudo-R^2	0.149	0.154	0.157	0.157	0.222
AIC	597.2	601.7	599.9	602.1	577.6

receive donations. Model specification (R.XI) shows the probit regression coefficients for a subsample excluding small banks in terms of average assets ($<$ 5 mn USD). The results of model specifications (R.VI)–(R.VIII) appear to be robust in terms of the CAMELS components, while the value of shares traded has a signifi-

Table 9: Robustness checks employing the FAILURE1 data set. Coefficients of the probit models based on model specification (V). The dependent variable is the FAILURE1 dummy. Model (R.VI) employs country-clustered standard errors, models (R.VII)–(R.XI) are performed using Eicker–Huber–White heteroskedastic-consistent errors. Standard errors are in parentheses. The symbols *, **, and *** express significance at the 10%, 5%, and 1% level, respectively. The variables are defined in Table 2.

		Additional financial market development controls		Subsample regressions		
	Country-clustered SE	Shares	Credit	Without NGOs	MFIs without donations	Without small MFIs
	(R.VI)	(R.VII)	(R.VIII)	(R.IX)	(R.X)	(R.XI)
CAMELS components						
CAP	−0.816***	−0.810***	−0.821***	−1.072***	−1.116***	−1.766***
	(0.270)	(0.232)	(0.234)	(0.308)	(0.298)	(0.552)
PAR30	0.858**	0.784**	0.848**	0.843**	1.091**	2.701**
	(0.372)	(0.398)	(0.402)	(0.410)	(0.515)	(1.068)
LLR	2.054*	1.966	2.079*	3.255**	2.712	1.060
	(1.193)	(1.224)	(1.241)	(1.350)	(2.221)	(2.946)
Borrowers per staff member (in thousand)	−0.200*	−0.207*	−0.197*	−0.170	−0.385**	−0.197
	(0.110)	(0.112)	(0.111)	(0.108)	(0.166)	(0.205)
ROA	−0.821**	−0.787*	−0.847**	−0.00207	−1.682*	−1.763
	(0.412)	(0.420)	(0.397)	(0.943)	(0.948)	(1.798)
Liquid assets	0.394	0.460	0.351	−0.164	0.409	0.540
	(0.752)	(0.681)	(0.655)	(0.857)	(1.097)	(1.546)
Deposits/Total Assets	−1.185***	−1.037***	−1.206***	−0.964**	−1.210**	−3.004***
	(0.296)	(0.380)	(0.367)	(0.440)	(0.481)	(0.652)
MFI-specific variables						
WB	0.862***	0.795*	0.883**	1.187**	0.291	0.988*
	(0.299)	(0.409)	(0.416)	(0.475)	(0.470)	(0.547)
Donations (dummy)	−0.276	−0.262	−0.293*	−0.365*		−0.440
	(0.175)	(0.160)	(0.163)	(0.203)		(0.310)
Regulated	−0.276	−0.292*	−0.275*	−0.235	0.204	−0.244
	(0.176)	(0.169)	(0.165)	(0.227)	(0.211)	(0.318)
NBdev	0.00769	0.00243	0.00890	0.00846	0.00814	0.321***
	(0.00665)	(0.00554)	(0.00601)	(0.00547)	(0.00674)	(0.0955)
Control variables						
logaAssets	0.190***	0.175***	0.194***	0.231***	0.260***	0.283***
	(0.0635)	(0.0435)	(0.0443)	(0.0568)	(0.0722)	(0.0901)
log(AVLS)	−0.0768	−0.0604	−0.0818	−0.0796	−0.258**	0.00159
	(0.120)	(0.0941)	(0.0977)	(0.110)	(0.124)	(0.141)
For-profit	−0.142	−0.0925	−0.146	−0.197	−0.126	−0.329
	(0.222)	(0.210)	(0.204)	(0.222)	(0.300)	(0.289)
TYPE_NGO	−0.561**	−0.539**	−0.552**		−0.405	−0.744**
	(0.246)	(0.219)	(0.222)		(0.324)	(0.361)
Region LAC	0.359	0.525	0.348	0.132	0.715*	0.113
	(0.334)	(0.332)	(0.313)	(0.414)	(0.392)	(0.470)
GDPpc (in thousand USD)	−0.168***	−0.182**	−0.166**	−0.226***	−0.134	−0.111
	(0.0590)	(0.0718)	(0.0687)	(0.0689)	(0.0830)	(0.0851)
GDP per capita growth (annual %)	0.0687**	0.0501	0.0681**	0.0579**	0.0928**	0.0576
	(0.0319)	(0.0313)	(0.0281)	(0.0254)	(0.0369)	(0.0411)
CropI	−0.0352***	−0.0382***	−0.0354***	−0.0335***	−0.0431***	−0.0351***
	(0.00828)	(0.00608)	(0.00587)	(0.00676)	(0.0104)	(0.0102)
Gini index	−0.00749	−0.0138	−0.00693	−0.0225	−0.0194	−0.00139
	(0.0159)	(0.0126)	(0.0119)	(0.0161)	(0.0147)	(0.0219)
Poverty rate	0.00764	0.00791	0.00659	0.0108	0.000979	0.00372
	(0.00848)	(0.00797)	(0.00786)	(0.00759)	(0.00916)	(0.0162)
Comp	−0.00355	−0.0123	−0.00157	−0.00223	0.00372	0.0259
	(0.0216)	(0.0169)	(0.0156)	(0.0203)	(0.0212)	(0.0302)
Value of shares traded		0.00666***				
		(0.00228)				
Domestic credit provided by banking sector			−0.00172			
			(0.00245)			
Constant	−0.483	0.167	−0.418	−0.734	0.845	−2.743
	(0.946)	(1.102)	(1.101)	(1.388)	(1.422)	(2.166)
Observations	1797	1797	1797	1140	885	762
Failures	39	39	39	28	24	20
Pseudo-R^2	0.240	0.251	0.240	0.294	0.292	0.373
AIC	331.8	329.7	333.6	229.6	200.1	162.1

cant positive effect on the probability of failure. Regarding microfinance-specific factors, our findings also prove to be consistent with our main results. Only the coefficient of the donations dummy and/or the regulation dummy is insignificant for several model specifications. The negative sign of the presence of donations indicates that either potential requirements by donors are met or that donors support MFIs facing financial distress. Due to the reduced sample size, in particular, the loss of several failures, the results of model specifications (R.IX)–(R.XI) should be interpreted carefully. Overall, the findings of the three subsample regressions appear to correspond well to the previous findings regarding FAILURE1. Model specification (R.XI) might be of special interest to investors intending to provide MFIs with large funding volumes, for example microfinance investment funds. The significant positive coefficient of NBdev in the subsample without small MFIs indicates that an excessive growth of MFIs may increase the probability of failure as hypothesized in H5.

The failure probability could be different for MFIs with high data quality compared to MFIs with low data quality, because MFIs with low data quality could tend to withhold information regarding the possibility of failure. To examine this effect, we construct an index based on 17 MFI-specific variables obtained from MIX Market that are important for our analysis. This data quality indicator, DQI, represents the portion of these variables that is missing for each MFI. A value for DQI of zero implies that none of the 17 figures is missing and the respective MFI exhibits a very high quality of data.

Table 10: Robustness checks considering data quality effects employing the FAILURE1 data set. Coefficients of the probit models based on model specification (V). The dependent variable is the FAILURE1 dummy. The regression for model (R.XII) is performed using Eicker–Huber–White heteroskedastic-consistent errors. The other regressions employ DQI-clustered standard errors. Standard errors are in parentheses. In model (R.XIV) the clusters are categorized in the following five groups: $0 \leq \text{DQI} < 0.0196$, $0.0196 \leq \text{DQI} < 0.1176$, $0.1176 \leq \text{DQI} < 0.2353$, $0.2353 \leq \text{DQI} < 0.3529$, and $\text{DQI} \geq 0.3529$. In model (R.XV) the clusters are classified in the following six groups: $0 \leq \text{DQI} < .0196$, $0.0196 \leq \text{DQI} < 0.1176$, $0.1176 \leq \text{DQI} < 0.2157$, $0.2157 \leq \text{DQI} < 0.3137$, $0.3137 \leq \text{DQI} < 0.4118$, and $\text{DQI} \geq 0.4118$. The symbols *, **, and *** express significance at the 10%, 5%, and 1% level, respectively. The variables are defined in Table 2.

	(R.XII)	(R.XIII)	(R.XIV)	(R.XV)
	DQI indicators	Clustered SEs (4 DQI clusters)	Clustered SEs (5 DQI clusters)	Clustered SEs (6 DQI clusters)
CAMELS components				
CAP	−0.841***	−0.816***	−0.816***	−0.816**
	(0.232)	(0.268)	(0.253)	(0.336)
PAR30	0.911**	0.858	0.858	0.858
	(0.399)	(0.653)	(0.749)	(0.661)
LLR	2.252*	2.054*	2.054*	2.054**
	(1.241)	(1.240)	(1.071)	(0.971)
Borrowers per staff member (in thousand)	−0.211*	−0.200**	−0.200**	−0.200***
	(0.120)	(0.0787)	(0.0900)	(0.0742)
ROA	−0.836**	−0.821	−0.821	−0.821
	(0.387)	(0.684)	(0.617)	(0.554)
Liquid assets	0.528	0.394	0.394***	0.394
	(0.675)	(0.264)	(0.139)	(0.261)
Deposits/Total Assets	−1.234***	−1.185**	−1.185***	−1.185***
	(0.415)	(0.501)	(0.354)	(0.441)
MFI-specific variables				
WB	0.811**	0.862***	0.862*	0.862**
	(0.401)	(0.325)	(0.463)	(0.391)
Donations (dummy)	−0.290	−0.276	−0.276*	−0.276*
	(0.177)	(0.180)	(0.166)	(0.144)
Regulated	−0.263	−0.276*	−0.276*	−0.276
	(0.164)	(0.161)	(0.161)	(0.177)
NBdev	0.00872	0.00769**	0.00769**	0.00769*
	(0.00581)	(0.00336)	(0.00385)	(0.00423)
Control variables				
logaAssets	0.198***	0.190***	0.190***	0.190***
	(0.0520)	(0.0385)	(0.0326)	(0.0324)
log(AVLS)	−0.0819	−0.0768	−0.0768	−0.0768
	(0.0947)	(0.108)	(0.0984)	(0.0688)
For-profit	−0.160	−0.142	−0.142	−0.142
	(0.207)	(0.0890)	(0.186)	(0.125)
TYPE_NGO	−0.581***	−0.561***	−0.561***	−0.561***
	(0.224)	(0.0442)	(0.123)	(0.155)
Region LAC	0.359	0.359	0.359*	0.359***
	(0.317)	(0.299)	(0.203)	(0.110)
GDPpc (in thousand USD)	−0.172***	−0.168*	−0.168**	−0.168**
	(0.0655)	(0.0953)	(0.0727)	(0.0820)
GDP per capita growth (annual %)	0.0686**	0.0687*	0.0687**	0.0687*
	(0.0308)	(0.0356)	(0.0321)	(0.0351)
CropI	−0.0343***	−0.0352***	−0.0352***	−0.0352***
	(0.00592)	(0.00788)	(0.00737)	(0.00615)
Gini index	−0.00420	−0.00749	−0.00749	−0.00749
	(0.0119)	(0.0173)	(0.0133)	(0.0119)
Poverty rate	0.00603	0.00764	0.00764	0.00764
	(0.00774)	(0.00577)	(0.00567)	(0.00519)
Comp	−0.00172	−0.00355	−0.00355	−0.00355
	(0.0174)	(0.00791)	(0.0159)	(0.0108)
Very high DQ (DQI< 0.0392)	0.152			
	(0.305)			
High DQ ($0.0392 \leq \text{DQI} < 0.1961$)	0.118			
	(0.298)			
Moderate DQ ($0.1961 \leq \text{DQI} < 0.3235$)	0.435			
	(0.268)			
Constant	−0.918	−0.483	−0.483	−0.483
	(1.241)	(1.518)	(1.447)	(0.978)
Observations	1797	1797	1797	1797
Failures	39	39	39	39
Pseudo-R^2	0.249	0.240	0.240	0.240
AIC	334.3	291.8	293.8	295.8

Table 10 shows the results for model specifications including dummy variables for various categories of data quality (very high, high, and moderate) with low data quality as reference category. Furthermore, this table presents regressions with DQI-clustered standard errors. Model specification (R.XIII) considers four clusters corresponding to the four categories in model specification (R.XII). The model specifications (R.XIV) and (R.XV) account for five and six DQI-clusters, respectively. While the inclusion of data quality dummies has no effect on our conclusions regarding the CAMELS components and microfinance-specific aspects, DQI-clustered standard errors lead to insignificant coefficients for the ROA and PAR30. However, the signs of the coefficients remain unchanged. For the microfinance-specific variables, we observe a significant positive effect of NBdev on the probability of failure in all three model specifications with DQI-clustered standard errors. Moreover, the negative sign of regulation is significant in model specifications (R.XIII) and (R.XIV), and the coefficient of the donations dummy shows a significant negative sign in (R.XIV) and (R.XV). Therefore, we are able to detect certain evidence to support H5 in the robustness analyses regarding data quality effects.

Table 11 investigates the impact of endogeneity issues that could arise regarding ROA. Note that in all regressions MFI cost factors are captured indirectly via the ROA. In particular, the cost factor financial expenses can be considered to be a source of endogeneity because creditors typically set the interest rates in a way to account for expected losses. To deal with this possible endogeneity, we perform probit regressions with endogenous explanatory variables. The structural and the reduced form equations of the IV-probit models are estimated jointly using maximum likelihood. Column two of Table 11 presents a just-identified model,

Table 11: Robustness checks considering endogeneity issues employing the FAILURE1 data set. Estimated coefficients based on model specification (V). The dependent variable is the FAILURE1 dummy. Model specification (R.XVII) employs the operating expenses divided by average assets as sole instrumental variable. Model specification (R.XVIII) additionally considers the lending interest rate in a country. The regression is performed using Eicker–Huber–White heteroskedastic-consistent errors. Standard errors are in parentheses. The symbols *, **, and *** express significance at the 10%, 5%, and 1% level, respectively. The variables are defined in Table 2.

	(R.XVI)	(R.XVII)	(R.XVIII)
	Probit	IV-Probit (Just-identified model)	IV-Probit (Over-identified model)
CAMELS components			
CAP	−0.793***	−0.742***	−0.745***
	(0.235)	(0.241)	(0.246)
PAR30	0.848**	0.829**	0.828**
	(0.405)	(0.404)	(0.405)
LLR	2.132*	1.999	1.995
	(1.239)	(1.276)	(1.281)
Borrowers per staff member (in thousand)	−0.200	−0.205*	−0.203*
	(0.127)	(0.123)	(0.123)
ROA	−0.776*	−1.107**	−1.096**
	(0.425)	(0.536)	(0.549)
Liquid assets	0.484	0.426	0.422
	(0.681)	(0.667)	(0.667)
Deposits/Total Assets	−1.132***	−1.122***	−1.121***
	(0.367)	(0.371)	(0.371)
MFI-specific variables			
WB	0.837**	0.837**	0.841**
	(0.408)	(0.409)	(0.409)
Donations (dummy)	−0.328**	−0.348**	−0.346**
	(0.166)	(0.165)	(0.165)
Regulated	−0.289*	−0.286*	−0.286*
	(0.165)	(0.165)	(0.165)
NBdev	0.0443	0.0409	0.0412
	(0.0365)	(0.0372)	(0.0375)
Control variables			
logaAssets	0.187***	0.194***	0.195***
	(0.0456)	(0.0436)	(0.0427)
log(AVLS)	−0.0851	−0.0900	−0.0903
	(0.0982)	(0.0981)	(0.0974)
For-profit	−0.159	−0.167	−0.166
	(0.208)	(0.205)	(0.206)
TYPE_NGO	−0.595***	−0.599***	−0.600***
	(0.226)	(0.224)	(0.224)
Region LAC	0.353	0.351	0.351
	(0.318)	(0.315)	(0.316)
GDPpc (in thousand USD)	−0.173**	−0.176**	−0.176**
	(0.0710)	(0.0708)	(0.0701)
GDP per capita growth (annual %)	0.0735**	0.0736**	0.0735**
	(0.0311)	(0.0308)	(0.0311)
CropI	−0.0355***	−0.0354***	−0.0357***
	(0.00625)	(0.00623)	(0.00627)
Gini index	−0.00471	−0.00538	−0.00553
	(0.0122)	(0.0120)	(0.0120)
Poverty rate	0.00729	0.00750	0.00764
	(0.00831)	(0.00832)	(0.00841)
Comp	−0.00620	−0.00414	−0.00431
	(0.0172)	(0.0162)	(0.0164)
Constant	−0.404	−0.458	−0.440
	(1.112)	(1.121)	(1.127)
Observations	1642	1642	1642
Failures	39	39	39
Wald test of exogeneity (p-value)		0.4335	0.4832

in which we employ the operating expenses divided by average assets as an instrumental variable. This is economically sound because operating expenses are

usually not driven by the solvency of an MFI. Furthermore, we investigate an over-identified model with the lending interest rate in the country in which the MFI operates as an additional instrumental variable. Because ROA is the dependent variable in the first-stage regression in the models with endogenous regressors, we drop all observations with imputed values for ROA. The resulting data set consists of 1642 MFIs, while none of the observations from MFIs that have failed is lost. Column one of Table 11 exhibits estimated coefficients for the standard probit model employing this reduced data set. In the resulting probit models with endogenous regressors, the conclusions regarding H1–H5 are robust compared to model (V). Solely the positive coefficient of LLR is insignificant. However, the high p-values of the Wald test of exogeneity in the IV-probit models indicate that standard probit regressions appear to be more appropriate.

3.4. Discussion

As our results indicate, the factors driving failures of MFIs are similar to traditional banks. The significant negative relationship between the capital asset ratio and the likelihood of failure is consistent with studies examining financial distress (e.g. Wheelock and Wilson, 2000; Koetter et al., 2007; Arena, 2008; Jin et al., 2011; Kerstein and Kozberg, 2013). Additionally, our results show a significant positive effect of (bad) asset quality, already detected in several previous studies on the failures of traditional banks (e.g., Cole and Gunther, 1998; Wheelock and Wilson, 2000; Kerstein and Kozberg, 2013). Our findings on the measure for earnings significantly show the expected negative sign. This relationship has also been determined, for example, by Cole and Gunther (1998), Koetter et al. (2007), Arena (2008), Cole and White (2012), and Kerstein and Kozberg (2013) for traditional banks.

While we are not able to identify a significant relationship between the liquidity and the probability of failure, previous studies on commercial banks show mixed results for this CAMELS component. For example, Koetter et al. (2007) find a significant positive relationship (for distressed targets). However, the respective findings of Arena (2008) are not significant for the sample of Latin American banks. Similarly, Koetter et al. (2007) obtain insignificant results concerning liquidity for distressed acquirers. Regarding the described varying previous findings for commercial banks, we conclude that, although insignificant, our finding for the liquidity as a predictor for failure is in accordance with the results of studies on traditional banks' failures.

In contrast to Kerstein and Kozberg (2013), our findings show a significant negative relationship between the ratio of deposits to total assets and the failure probability. However, our results considering the sensitivity to market risk are consistent with H1. Overall, our results seem to be consistent with previous literature on traditional banks.

Additionally, we obtain results concerning the influence of MFI-specific variables. The failure probability increases with a higher ratio of female customers. This finding is in line with Hermes et al. (2011), who detect a negative relationship between female borrowers and efficiency of the MFI. Our main results in Table 7 and several robustness analyses show that, depending on the respective model specification or subsample employed, regulation, the presence of donations, and the growth of the MFIs could also affect the probability of failure. Specifically, regulation and donations seem to reduce the likelihood of failure, while a too fast growth is associated with an increasing failure probability. Overall, we are able to confirm H2, but we also observe evidence in favour of H3–H5.

4. Conclusion

Although being of high importance for microfinance actors and the academic community, the subject of MFI failures has so far been under-researched. In this article, we study the determinants of failures based on the CAMELS components, microfinance-specific variables, and several control variables using a categorical regression model with probit specification and apply Eicker–Huber–White heteroskedastic-consistent standard errors. Our findings confirm that many results from standard banking studies are also applicable to MFIs, with the main result in this regard being that of the CAMELS components the capital adequacy (C), the asset quality (A), the management capability (M), the earnings (E), and the sensitivity to market risk (S) can be confirmed as being explanatory factors of the probability of failure.

Regarding MFI-specific variables, the percentage of female borrowers appears to have a positive influence on the failure probability. Our results also indicate a significant relationship between the other microfinance-specific variables and the probability of failure in several model specifications. For example, we find evidence of a negative influence on the failure probability concerning the regulation and the presence of donations, as well as a positive influence of the growth of an MFI. Although we do not have any concrete indications, it is possible that remaining endogeneity problems in our data set could also exist.

We can derive several policy implications from our findings. First, the result that regulation appears to lower the probability of failure can be interpreted as a recommendation for policy makers to implement mechanisms that increase the share of regulated MFIs. Second, our results indicate that rapid growth of MFIs should be observed critically by regulators and other stakeholders. The same ad-

vice applies to MFIs with a high share of female borrowers as these MFIs are also more susceptible to failure risk.

As suggestions for further research we would like to point to the fact that in the recent years dating from 2011 onwards, there are indications of further failures of MFIs not contained in our sample. Once these data can be utilized it would make sense to set up new categories for failures, i.e. classical debt default and closures by the regulatory authority. From an investor perspective, for the case of defaults it would be very interesting to analyse the losses accompanying the respective failures. Finally, the findings of this paper can be integrated into credit risk models, which are of increasing importance for microfinance investors and intermediaries initiating and managing microfinance investment vehicles.

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Appendix A. Technical details on failure classification

We classify MFIs as failed, non-failed, and unsolved with respect to a reference year *RY* and in accordance with the two failure definitions shown in Section 2.2, where the reference year is the point in time with a failure indication.

Classification algorithm for failures according to the strict definition (FAILURE1).

(1) If the MFI stopped reporting to MIX Market at some point in time t (t refers to the year after the last report), continue, else go to step (2).

   (a) If there are signs for bankruptcy, restructuring, closing of the MFI by a regulatory authority in t or afterwards, then set FAILURE1 $= 1$, $RY = t$, else continue.

   (b) If the MFI was subject to a merger in t or afterwards, continue, else go to step (c).
   If the MFI's $CAR_{t-1} \leq 0.02$ (indicates a merger after financial distress), then set FAILURE1 $= 1$, $RY = t-1$. Else, set FAILURE1 $= 0$, $RY = t$.

(c) If there are other reasons for the break in the MFIs reporting history or evidence that the MFI still operates, then set FAILURE1 $= 0$, $RY = t$, else continue.

(d) If the reasons for the break in the MFIs reporting history cannot be solved, then the MFI is classified as unsolved.

(2) If the MFI was subject to a restructuring at some point in time t, then set FAILURE1 $= 1$, $RY = t$, else set FAILURE1 $= 0$, $RY = 2011$.

The situation of several MFIs examined remained unsolved (1.d) either due to lack of availability of information or because the information could not be evaluated for linguistic reasons. Furthermore, we examined two MFIs reporting a capital asset ratio of zero to MIX Market more closely. For one of these MFIs rating reports for the respective years have been available. These rating reports showed values for the capital asset ratio that were different from the values reported to MIX Market. We classify this MFI as unsolved.

Classification algorithm for failures according to the extended definition (FAILURE2).

(1) Generate FAILURE1 according to the algorithm shown above.

(2) If FAILURE1 $= 1$ then set FAILURE2 $= 1$, $RY = RY_{\text{FAILURE1}}$. Else, continue.

(3) If $CAR_t \leq 0.02$ for some point time t and all periods afterwards, then set FAILURE2 $= 1$, $RY = t$. Else, set FAILURE2 $= 0$, $RY = 2011$.

Appendix B. Additional tables (not for publication)

Table B.12: Absolute and relative frequencies for categorical variables based on the unimputed data sets for the strict definition of failure (FAILURE1) and unsolved cases. The variables are defined in Table 2.

	FAILURE1 (without unsolved cases)		Unsolved cases (excluded from FAILURE1)	
	absolute	relative	absolute	relative
Type				
Bank	161	0.09	4	0.02
Credit Union	300	0.17	106	0.40
NBFI	515	0.29	49	0.19
NGO	657	0.37	57	0.22
Other	164	0.09	48	0.18
Region				
Africa	450	0.25	60	0.23
East Asia and the Pacific	220	0.12	44	0.17
Eastern Europe and Central Asia	272	0.15	111	0.42
Latin America and The Caribbean	455	0.25	15	0.06
Middle East and North Africa	73	0.04	2	0.01
South Asia	327	0.18	32	0.12
Regulated				
No	672	0.37	110	0.42
Yes	1047	0.58	141	0.53
No information	78	0.04	13	0.05
Operational self-sufficiency				
No	535	0.30	76	0.29
Yes	1153	0.64	175	0.66
No information	109	0.06	13	0.05
Profit status				
Non-profit	1,012	0.56	154	0.58
Profit	681	0.38	65	0.25
No information	104	0.06	45	0.17
Deposits				
No	614	0.34	53	0.20
Yes	1006	0.56	130	0.49
No information	177	0.10	81	0.31
Donations				
No	885	0.49	141	0.53
Yes	747	0.42	98	0.37
No information	165	0.09	25	0.09
Total	1,797	1.00	264	1.00

Table B.13: Descriptive statistics for metric variables based on the unimputed data set for the strict definition of failure, FAILURE1 (Panel A) and the unsolved cases (Panel B). The variables are defined in Table 2.

				Quantiles				
Variable	n	Mean	S.D.	Min	0.25	Mdn	0.75	Max
Panel A: FAILURE1	1797							
CAP	1758	0.314	0.291	−3.639	0.137	0.243	0.457	1.000
WOR	1542	0.022	0.048	−0.010	0.000	0.006	0.023	0.577
LLR	1620	0.018	0.046	−0.323	0.000	0.003	0.018	0.563
PAR30	1572	0.081	0.126	0.000	0.017	0.046	0.094	2.350
PAR90	1401	0.055	0.085	0.000	0.009	0.029	0.063	0.933
OE	1641	0.195	0.181	0.000	0.095	0.145	0.236	2.782
Borrowers per staff member	1724	134.723	259.006	0.000	56.000	101.000	157.167	8191.667
ROA	1642	−0.009	0.154	−2.930	−0.016	0.015	0.043	0.577
Profit margin	1662	−0.098	0.753	−9.656	−0.100	0.086	0.194	1.423
NOI	1666	−0.008	0.152	−2.930	−0.018	0.018	0.048	0.485
Deposits/Total Assets	1590	0.244	0.288	0.000	0.000	0.107	0.466	0.973
Liquid assets	1517	0.170	0.131	0.000	0.080	0.136	0.222	0.846
NB (in thousands)	1747	56.982	361.502	0.000	1.634	6.579	23.036	7498.742
NBdev	1514	0.415	3.823	−0.966	−0.022	0.109	0.320	142.000
Assets (mn USD)	1767	36.337	167.286	0.000	0.900	3.276	13.738	3553.838
AVLS	1735	1133.627	1816.088	1.000	156.500	440.333	1260.500	14825.000
Donations/Average Assets	1644	0.037	0.149	−0.035	0.000	0.000	0.010	3.472
WB	1537	0.637	0.267	0.000	0.424	0.623	0.897	1.000
DQI	1797	0.176	0.192	0.000	0.000	0.118	0.314	0.941
GDPpc	1784	2715.224	2753.615	121.014	762.747	1251.168	3865.162	17142.119
Comp	1793	6.660	4.403	1.000	3.442	5.161	10.754	21.839
CropI	1782	109.752	13.199	62.140	102.335	109.130	116.360	215.285
Poverty rate	1061	32.652	12.927	2.900	24.900	32.367	39.800	80.700
Domestic credit provided by financial sector	1706	45.410	30.387	−19.142	22.695	42.006	60.829	184.570
Value of shares traded	1289	20.300	32.806	0.002	1.102	4.386	20.398	157.419
Gini index	1106	42.238	8.693	26.975	33.380	42.980	48.713	67.400
Lending interest rate	1449	15.441	9.514	5.396	10.833	13.783	17.973	203.961
GDP per capita growth (annual %)	1784	3.370	2.854	−9.410	1.303	3.263	4.987	21.722

				Quantiles				
Variable	n	Mean	S.D.	Min	0.25	Mdn	0.75	Max
Panel B: Unsolved Cases	264							
CAP	259	0.323	0.370	−2.966	0.118	0.243	0.525	1.000
WOR	227	0.008	0.026	0.000	0.000	0.000	0.005	0.220
LLR	237	0.032	0.372	−0.042	0.000	0.000	0.004	5.717
PAR30	232	0.077	0.116	0.000	0.009	0.039	0.092	0.865
PAR90	172	0.055	0.087	0.000	0.004	0.023	0.066	0.546
OE	242	0.213	0.291	0.000	0.077	0.135	0.229	2.479
Borrowers per staff member	246	91.636	101.187	0.000	30.000	52.417	122.500	617.000
ROA	243	0.000	0.246	−2.153	−0.015	0.023	0.075	0.476
Profit margin	218	−0.035	0.806	−7.730	−0.061	0.132	0.273	0.728
NOI	218	0.013	0.231	−2.473	−0.012	0.031	0.078	0.457
Deposits/Total Assets	182	0.414	0.357	0.000	0.000	0.382	0.765	0.986
Liquid assets	173	0.133	0.142	0.000	0.028	0.084	0.174	0.757
NB (in thousands)	251	4.469	15.095	0.000	0.287	0.913	3.204	180.828
NBdev	171	0.577	2.319	−0.829	−0.046	0.105	0.457	24.250
Assets (mn USD)	260	1.985	4.266	0.000	0.167	0.771	1.989	46.166
AVLS	243	1646.481	2556.438	1.000	166.000	698.000	1953.000	14865.667
Donations/Average Assets	237	0.073	0.289	0.000	0.000	0.000	0.014	2.666
WB	227	0.588	0.260	0.000	0.418	0.585	0.766	1.000
DQI	264	0.274	0.171	0.000	0.176	0.275	0.353	0.882
GDPpc	263	3484.404	3689.310	100.818	707.506	1567.536	6511.967	10423.319
Comp	263	5.638	3.582	1.157	3.162	4.463	6.995	15.812
CropI	264	105.574	8.476	69.933	100.000	106.005	110.413	143.547
Poverty rate	151	30.022	16.743	8.900	16.600	27.600	39.900	72.000
Domestic credit provided by banking sector	248	37.690	28.883	0.783	23.010	28.323	46.047	172.083
Value of shares traded	232	26.157	29.161	0.010	2.209	18.054	45.953	171.990
Gini index	176	39.472	6.201	28.190	34.010	40.760	42.990	58.627
Lending interest rate	211	16.593	9.887	5.310	11.129	13.730	17.454	66.885
GDP per capita growth (annual %)	263	4.439	3.047	−13.080	2.209	4.572	7.100	21.722

Table B.14: Descriptive statistics for metric variables based on the imputed data set for the strict definition of failure (FAILURE1). The variables are defined in Table 2.

				Quantiles				
Variable	n	Mean	S.D.	Min	0.25	Mdn	0.75	Max
Panel C: Full sample	1797							
CAP	1797	0.314	0.288	−3.639	0.138	0.251	0.450	1.000
WOR	1797	0.022	0.045	−0.010	0.000	0.010	0.022	0.577
LLR	1797	0.018	0.043	−0.323	0.000	0.006	0.018	0.563
PAR30	1797	0.081	0.117	0.000	0.020	0.055	0.083	2.350
PAR90	1797	0.055	0.075	0.000	0.014	0.044	0.055	0.933
OE	1797	0.195	0.173	0.000	0.099	0.156	0.222	2.782
Borrowers per staff member	1797	134.723	253.688	0.000	58.000	104.667	153.500	8191.667
ROA	1797	−0.009	0.147	−2.930	−0.011	0.012	0.039	0.577
Profit margin	1797	−0.098	0.724	−9.656	−0.098	0.069	0.182	1.423
NOI	1797	−0.008	0.146	−2.930	−0.013	0.014	0.045	0.485
Deposits/Total Assets	1797	0.244	0.271	0.000	0.000	0.169	0.405	0.973
Liquid assets	1797	0.170	0.121	0.000	0.090	0.164	0.203	0.846
NB (in thousands)	1747	56.982	361.502	0.000	1.634	6.579	23.036	7498.742
NBdev	1797	0.415	3.509	−0.966	0.000	0.176	0.414	142.000
Assets (mn USD)	1767	36.337	167.286	0.000	0.900	3.276	13.738	3553.838
AVLS	1797	1133.794	1784.466	1.000	161.500	474.667	1228.667	14825.000
Donations/Average Assets	1797	0.037	0.143	−0.035	0.000	0.000	0.025	3.472
WB	1797	0.637	0.247	0.000	0.463	0.637	0.850	1.000
DQI	1797	0.176	0.192	0.000	0.000	0.118	0.314	0.941
GDPpc	1797	2715.229	2743.631	121.014	762.747	1251.168	3865.162	17142.119
Comp	1797	6.660	4.398	1.000	3.478	5.170	10.754	21.839
CropI	1797	109.752	13.144	62.140	102.350	109.260	116.360	215.285
Poverty rate	1797	32.652	9.931	2.900	29.800	32.652	34.400	80.700
Domestic credit provided by banking sector	1797	45.412	29.608	−19.142	24.011	44.387	60.829	184.570
Value of shares traded	1797	20.330	27.782	0.002	2.063	14.198	20.406	157.419
Gini index	1797	42.238	6.818	26.975	39.790	42.238	45.530	67.400
Lending interest rate	1797	15.439	8.543	5.396	11.278	14.927	16.481	203.961
GDP per capita growth (annual %)	1797	3.370	2.844	−9.410	1.385	3.263	4.889	21.722

				Quantiles				
Variable	n	Mean	S.D.	Min	0.25	Mdn	0.75	Max
Panel D: Failed MFIs	39							
CAP	39	0.144	0.180	−0.206	0.058	0.120	0.245	0.713
WOR	39	0.032	0.049	0.000	0.000	0.016	0.034	0.243
LLR	39	0.031	0.048	−0.007	0.000	0.015	0.034	0.243
PAR30	39	0.121	0.119	0.000	0.033	0.081	0.175	0.438
PAR90	39	0.097	0.115	0.000	0.030	0.055	0.147	0.466
OE	39	0.199	0.158	0.019	0.089	0.134	0.290	0.666
Borrowers per staff member	39	164.859	131.862	16.500	74.000	134.723	224.000	466.333
ROA	39	−0.050	0.135	−0.509	−0.128	−0.015	0.038	0.177
Profit margin	39	−0.279	0.693	−2.489	−0.601	−0.097	0.124	1.024
NOI	39	−0.047	0.133	−0.450	−0.097	−0.008	0.042	0.185
Deposits/Total Assets	39	0.149	0.187	0.000	0.000	0.047	0.244	0.694
Liquid assets	39	0.198	0.138	0.007	0.102	0.170	0.272	0.692
NB (in thousands)	38	177.950	447.208	0.521	5.364	12.842	84.175	2233.332
NBdev	39	0.553	1.260	−0.490	−0.050	0.227	0.681	6.683
Assets (mn USD)	39	52.879	99.307	0.042	0.992	6.011	39.053	397.776
AVLS	39	793.850	1166.755	36.000	146.000	230.000	1089.667	4761.333
Donations/Average Assets	39	0.039	0.084	0.000	0.000	0.000	0.037	0.376
WB	39	0.727	0.252	0.130	0.595	0.693	1.000	1.000
DQI	39	0.154	0.156	0.000	0.000	0.118	0.294	0.471
GDPpc	39	1467.031	1722.690	255.298	447.961	1119.172	1176.748	9402.997
Comp	39	7.313	4.417	1.000	2.920	5.467	11.711	15.667
CropI	39	104.064	11.279	67.415	99.850	105.120	114.287	116.360
Poverty rate	39	34.437	8.191	9.000	29.800	32.652	38.800	61.700
Domestic credit provided by banking sector	39	46.704	27.684	2.402	17.268	60.016	70.341	96.037
Value of shares traded	39	32.336	29.636	0.002	7.388	20.406	76.168	85.057
Gini index	39	40.296	5.807	27.820	38.990	42.238	42.238	50.550
Lending interest rate	39	15.885	11.472	7.600	11.278	13.996	16.209	83.468
GDP per capita growth (annual %)	39	4.057	3.080	−5.900	1.947	3.932	5.729	8.834