Commitment of Microfinance Institutions and Survival Entrepreneurs Under Financial Distress

FERNANDO A. MOYA-DAVILA

Abstract: *Commitment leads directly to cooperative behavior, vital for long-term mutually beneficial relationships. When a relationship is weak and not considered in economic transactions, causing a Microfinance Institution (MFI) to disregard a survival entrepreneur's action, economic agents (i.e., the MFI and the entrepreneur) will lose economic rents. On the other hand, when a relationship is strong, and an entrepreneur's actions are observed, the resulting economic rents will be such that each party will be better off building a relationship and commitment than not building it. COVID-19 in 2020 and hurricane OTIS in 2023 gave us an extraordinary opportunity to measure the impact of commitment in the interaction of MFI and survival entrepreneurs. Based on 686,657 observations of credits from January 2020 to June 2021 during COVID-19 and 22,384 observations from September 2023 to February 2024 during OTIS23, granted by a Mexican MFI to groups of survival female entrepreneurs, this study analyzes how relaxing credit policies during financial distress times, positively affect entrepreneurs' commitment to the MFI. This means that building relationships and commitment creates and distributes value among economic agents.*

Keywords: Lending, financial intermediation, microfinance, entrepreneurship, commitment, COVID-19, hurricane OTIS, group lending, relationship lending

Fernando A. Moya-Davila, Tecnologico de Monterrey, EGADE Business School

Introduction

A very well-appreciated source of funding for survival entrepreneurs is microfinance. This unique source of credit targets entrepreneurs who do not fit into the traditional banking system. Microfinance Institutions (MFI) offer entrepreneurs microloans ranging from 100 to 500 USD. Even though interest rates are ridiculously high (80—120%), entrepreneurs benefit from the loans that translate, in most cases, into fresh working capital. Why working capital? It is the only financial decision that can provide a return in the short term that can pay the high interest rates charged by MFI. If survival entrepreneurs behave correctly by repaying the loan, more credit is available from the MFI. On the contrary, if entrepreneurs (borrowers) default, credit rationing (Stiglitz and Weiss, 1981) is present. The availability of future loans is conditional on the repayment of the current loan (Shapiro, 2015).

Microcredit is a financial service that provides micro loans to individuals or groups who lack access to banking services. These loans are often aimed at supporting entrepreneurial activities, small businesses, or personal needs, enabling borrowers to improve their economic situations and achieve financial independence. Microcredit is particularly significant in developing countries where access to conventional credit is limited. Microfinancing can be defined also as the movement that converts the poorest into the actors of their economic development through alternative financing (Yunus, 1999). The concept was popularized by organizations like the Grameen Bank in Bangladesh, founded by Nobel laureate Muhammad Yunus.

The mission of microfinance programs is to access a population with credit needs, to obtain and cover the economic resources for the development of the program, to obtain a high portfolio recovery rate, to lower operating costs through efficiency, and to gradually reduce dependence on the subsidy. In the most diverse cultures and countries: Bangladesh, India, Indonesia, Mexico, Perú, and Bolivia, microcredit programs have proven to be successful beyond all expectations.

Microfinance Institutions (MFIs) play a critical role in supporting survival entrepreneurs, particularly during financial distress. Survival entrepreneurs' activities consist primarily of street businesses. They do not even reach a brick-and-mortar facility. Street entrepreneurs execute economic transactions by selling their products and services directly to walking pageants. (Hansen, K. T., Little, W. E., & Milgram, B. L.,2014)

"They practice their economic activities on sidewalks, in office corridors, in aisles of public markets, around train and bus stations, and in vacant spaces where vendors sell fruits and vegetables, prepared foodstuffs, drinks, handicrafts, toiletries, items of hardware, pirated music CDs, new and secondhand clothes, shoes, books, and many other goods and services. These vendors set up temporary stalls in urban public spaces and move around with their goods, changing locations, strategies, and commodities, depending on the level of surveillance."

In 2020, the world lived a disruptive era facing an unusual enemy that distressed every single activity on the planet. The COVID-19 pandemic altered usual activities, routines, and livelihoods, and has had a significant impact on the survival of entrepreneurs' economy. COVID-19 pandemic restrictions imposed by government officials limited economic activities. Survival entrepreneurs were mostly affected by the restrictions causing those with a microloan to live in a distressful financial situation. Without income and facing debt payments, good borrowers had no choice but to default.

The COVID-19 pandemic and Hurricane Otis (2023) disrupted economic activities, exposing vulnerabilities in informal sectors. Street entrepreneurs, who operate without fixed facilities, faced severe income loss due to government-imposed lockdowns and natural disasters. To mitigate defaults, the MFI introduced a supportive program targeting entrepreneurs facing insolvency, reduced income, business closures, health crises, or restricted market access. This program included capital payment deferrals and interest forgiveness, contingent on demonstrated borrower effort. Such interventions underscore the interdependence between MFIs and entrepreneurs, where mutual commitment fosters resilience during crises.

To prevent default MFI[1] Started supportive programs to alleviate the distress of borrowers showing commitment to them but expecting reciprocity. This specific program installed by a particular MFI ran from May to December of 2020 and consisted of supporting community groups, depending on the health contingency period, may request one or more additional extensions, depending on the needs or the problems detected, however, for its subsequent application and authorization, it must be inquired whether the client, business, or activity present any of the following problems; insolvency due to low sales, reduction of income due to intermittent business opening, closure for being a non-essential activity, impossibility of access to a restricted population, no payment capacity. clients or family members of clients sick with COVID, businesses closed by government declaration.

The MFI is committed to Entrepreneurs by giving up to 3 months of payment for capital and forgiveness of 100% of default interest and up to 75% of ordinary interest according to the forgiveness system.

Under a committed transaction, a survival entrepreneur has the chance to receive extra help from the MFI if things do not go well. COVID-19 worsens the economy worldwide. The condition for an entrepreneur to receive extra help is to make sure that the MFI observes good behavior. Both MFI and entrepreneurs have incentives to be committed. In doing so, MFI will have the possibility to receive future higher payoffs by flexible lending policies to a distressed but hardworking entrepreneur. Entrepreneurs will benefit from the commitment relationship because, if things do not go well, thanks to the high effort exerted, the project will be supported by the MFI. The project will continue with high expectations of future better payoffs. If the MFI and the entrepreneur start an arm's length transaction, in bad times, the entrepreneur will

[1] The MFI that provided datasets for this research is SOFIPA. The author of this manuscript is part of the board of directors.

never receive extra help due to the impossibility of the MFI to observe the effort that the entrepreneur exerted (Moya, 2016).

Commitment is defined as the intention to continue a course of action or activity such as maintaining a relationship with a business partner (Fehr,1988). Commitment is a well-known construct in relationship marketing. Commitment is the most advanced phase of partners´ interdependence. As relationship increases, commitment increases. Commitment is a positive function of the relationship. Commitment is central to relational exchanges between the firm and its various stakeholders. Commitment leads directly to cooperative behavior which is vital for long-term mutually beneficial relationships. Commitment encourages cooperation among partners, emphasizes the long-term rather than short-term benefits of staying with existing relationships, and gives confidence that partners will not act opportunistically. Over time, the relationship between borrower and lender evolves into one of mutual commitment based on confidence, conviction, and reliance (Saparito et al. 2004). This trust makes it easier for the parties to be flexible and use discretion in renegotiating their contract when circumstances change (Berlin and Mester, 1992).

Disruptive events like the COVID-19 pandemic give opportunities to test if commitment from both sides, borrower, and lender, is present in economic transactions. A "before" and "after" of policy installments can directly measure commitment behavior and test if this cooperative behavior delivers long-term mutual benefits.

Another disruptive event that allowed testing commitment was Hurricane Otis. In 2023, Hurricane Otis hit the port of Acapulco, Mexico with full force during the first minutes of October 25, with wind gusts of more than 300 kilometers per hour. The meteorological phenomenon went from tropical storm to category five hurricane in just 24 hours, an unprecedented acceleration that generated surprise among specialists.

The port was left without basic services, such as electricity and water, and was completely cut off from communication, without supplies of fuel, medicine, and food; traffic was difficult with streets full of debris and without materials to repair the damage. Acapulco was for several weeks a disaster zone.

At least 250,000 families have received help from the government, with an investment of 61 billion pesos, but for many inhabitants, the progress in the reconstruction has been at their own expense.

Without a doubt, Hurricane Otis, the most powerful hurricane to make landfall in the Mexican Pacific, changed the image of the paradisiacal resort. The port is one before and one after it.

In this study, a theoretical framework on the Commitment phenomena of MFI and Survival Entrepreneurs is developed. the research question "Commitment creates mutual benefits to borrower and lender?" is discussed, it is added to prior research that has examined the effects of the MFI-Survival entrepreneur relationship, it contributes to a better understanding of how new policies from MFI that relieve survival entrepreneurs create value for both parties.

This study integrates three theoretical frameworks; Resource Dependence Theory: Explains how survival entrepreneurs and MFIs rely on each other for financial resources and stability, particularly during crises. Organizational Stress Theory: Highlights how external shocks (e.g., pandemics, disasters) strain MFI-entrepreneur relationships, testing their adaptive capacity. Theory of Entrepreneurial Economics: Contextualizes survival entrepreneurs' high-risk, informal operations and their reliance on microloans for working capital.

These theories collectively frame the study's exploration of commitment as a mechanism to mitigate resource asymmetry and stress in financial transactions.

Literature Review

Lending and borrowing

Lending and borrowing money are fascinating fields of research. The economic transaction does not end in t=0 when the money is lent. As for any other commercial transaction, the story ends when money is exchanged for any product or service. When lending, the economic transaction ends when paying in full, the principal and interest, in the future. The borrower receives money from a lender in the current period with certain conditions that are set also in the current period. In the future, the borrower will pay back interest and principal. The lender is not sure if the borrower will make such payments. Information asymmetries and moral hazard exist in this transaction. The characteristics and the future actions of the borrower are uncertain for the lender. It is a human behavioral science.

A type of lending that diminishes the bad behavior of the borrower is relationship lending. Relationship lending is one solution to alleviate the information asymmetries and moral hazards that lenders have with borrowers. Modern financial intermediation research has focused its attention on the role that relationship plays in the lender-borrower interaction. As information asymmetries are critical for financial intermediation at all levels of lending, especially for entrepreneurs, relationship lending has been considered an alternative type of lending to diminish this problem. Diamond (1984) pointed out well by saying that the best lending practice by depositors is to have delegated monitoring by lenders because they have diversification possibilities. Lenders bear most of the risk of lending. How do they know to whom to lend it? What are the probabilities of the borrower paying the loan back on time? Boot and Thakor (1994) argue that if entrepreneurs perform well with the first credit, he or she will obtain infinite unsecured credits. Building a relationship helps for future credits from lenders to borrowers.

Rajan (1992) and Boot (2000) emphasize that relationship lending allows lenders to develop "soft information" that cannot be easily quantified or transferred to other institutions. This information is crucial for making lending decisions that rely less on hard, publicly available data and more on qualitative assessments of the borrower's prospects.

Berger and Udell (1995) demonstrate that relationship lending lowers the cost of credit for SMEs by improving information flow and reducing risk premiums. Likewise, Petersen and Rajan (1994) observe that firms with strong banking relationships benefit from increased credit availability and more favorable loan terms.

Additionally, relationship lending can enhance loan performance. Cole (1998) reports that banks with stronger relationships with their borrowers see lower default rates because they can better monitor and support their clients. This perspective is corroborated by Elsas and Krahnen (1998), who find that relationship lending by German banks boosts the survival rates of firms during economic downturns.

Recent literature on relationship lending confirms old empirical evidence. Moya (2019) finds that relationship lending by a Mexican bank creates incentives while facilitating monitoring and screening because it overcomes the information asymmetries and moral hazard problems that a transaction between lender and borrower carries. Moya and Rajagopal (2020) conclude that social ties and a stronger relationship built between a Microfinance Institution and a group of female borrowers determine better repayment performance.

Microfinance

The concept of microfinance can be traced back to the 1970s with the work of Muhammad Yunus in Bangladesh. MFIs have proliferated worldwide. Studies such as Armendáriz and Morduch (2010) highlight the transformation from small-scale, community-based lending models to more structured and commercially viable institutions, driven by the dual goals of social impact and financial sustainability.

MFIs are primarily recognized for their role in poverty alleviation and economic development. The truth is that this is a very romantic view. Realistically, what MFIs can accomplish is to include the poor in a financial system and take them to the next level of financing. In other words, prepare the poor to request financing from banks and other type of financial intermediation rather than MFIs. Studies have documented the effects of microfinance on income generation and employment, particularly among women. Khandker (2005) found that access to microfinance reduced poverty levels in rural Bangladesh.

Microfinance Institutions (MFIs) provide credit to the poor. The size of the loan is smaller than those granted by banks. These types of loans are also known as microcredit. The type of borrowers of an MFI are often survival entrepreneurs in need of economic support for their financial needs. Survival entrepreneurs are considered too risky by traditional banks because they cannot provide collateral and because they tend to work in the informal sector of the economy. The collateral is mostly the relationship they sustain with the MFI[2]. MFI play a crucial role in the financial inclusion landscape of developing countries such as México, India, Perú, Bolivia, Guatemala, etc. If the survival entrepreneur defaults, the relationship is jeopardized and will find no other source of financing.

[2] I want to thank Jorge Ramos, professor at EGADE Business School, for this insightful idea.

The impact of MFIs is commonly criticized and questioned. Bateman (2010) argues that while microfinance can provide short-term financial relief, it may also lead to debt cycles and over-indebtedness among borrowers. The mixed outcomes necessitate a nuanced understanding of the contexts in which MFIs operate and the mechanisms they employ.

Financial inclusion is a mandate of MFIs, integrating the poor into the formal financial system. Cull, Demirgüç-Kunt, and Morduch (2009) emphasize the role of MFIs in providing access to credit, savings, insurance, and other financial services, which are crucial for economic resilience and growth. Additionally, MFIs often promote social outcomes such as improved education, healthcare access, and women's empowerment, as documented by studies like Pitt and Khandker (1998).

Despite their successes, MFIs have faced criticisms regarding high interest rates, and the potential for exacerbating poverty. Studies by Guérin, Morvant-Roux, and Villarreal (2014) discuss the adverse effects of microfinance, including increased financial vulnerability and social tensions. These critiques call for more responsible and ethical practices within the microfinance sector.

Commitment

Commitment is a construct studied across various disciplines, mostly in social sciences. It is broadly understood as a psychological state that characterizes an individual's attachment to an entity, whether it be a relationship, organization, or goal.

Research has identified various factors influencing commitment. In business, a crucial factor identified is the perceived organizational support. Gabay-Mariani, et al., (2024) show that affective commitment is a necessary condition for entrepreneurs to conduct overinvesting behaviors.

There are various types of commitment that literature distinguish. In romantic relationships, Johnson’s (1991) framework differentiates between personal commitment (desire to maintain a relationship), moral commitment (sense of obligation), and structural commitment (constraints preventing exit). This study relies on both types. A desire to maintain a relationship due to a sense of obligation. In personal relationships, strong commitment is associated with relationship stability, satisfaction, and resilience to conflict (Rusbult et al., 1998).

Cultural context significantly influences commitment. Research by Hofstede (1980) indicates that cultural dimensions such as individualism versus collectivism impact how commitment is perceived and manifested. In collectivist cultures, such as southern Mexican states, normative and affective commitments might be stronger due to the emphasis on group harmony and loyalty.

Commitment is a complex construct essential to understanding various human behaviors. While significant progress has been made in identifying how commitment is manifested, ongoing research is necessary. Understanding the implication of commitment across different business contexts will enhance its applications.

The datasets and the hypotheses

The MFI that provided the data is in the Mexican state of Oaxaca. It has operations in five different states: Oaxaca, Puebla, Guerrero, Mexico City, and Michoacán. Acapulco is in the state of Guerrero. The dataset was provided on two different date ranges. The Mexican MFI provided the first dataset of 686,657 observations of credits given to 65,532 female individuals belonging to 4,509 different groups.[3] From January 2020 to June 2021. The average credit was 5,670 pesos[4] (320 USD). The average annual nominal interest rate was 120%. This first dataset was used to analyze commitment under COVID-19. The second dataset consisted of 22,384 observations of credits given to 5,346 female individuals belonging to 741 different groups from September 2023 to March 2024. The average credit was 5,376 pesos (303 USD). The average annual nominal interest rate was 126%. This second dataset was used to analyze commitment under the OTIS hurricane tragedy.

Information provided to analyze commitment during the pandemic covered one hundred percent of clients of MFI. The phenomenon affected the whole credit portfolio. The lockdown demanded to stay at home diminishing almost to zero cash income of entrepreneurs. With families to feed and with debt owed to the MFI, new temporary credit policies were introduced. The dataset considers information two months before the lockdown from January 2020 to June 2021. A lockdown in Mexico was ruled in March of 2020. For this analysis, all credits that defaulted before May 2020 were eliminated, taking out any other reason for defaulting than the COVID-19 effect. It is notorious how monthly payments decreased, or default increased the same months the lockdown started (Graph 1). COVID-19 policies were installed in May 2020 and were discussed in the introduction section of this paper.

Information provided to analyze commitment during Hurricane OTIS covered a fraction of clients of MFI. The phenomenon affected a small portion of the credit portfolio, only in the Acapulco region. Still, the dataset had enough information to run a statistically valid analysis. The regional economy experienced a shutdown as tourism was prevented from visiting Acapulco. As in COVID-19, survival entrepreneurs had families to feed and with debt owed to the MFI new temporary credit policies were introduced. The dataset considers information two months before the disaster, from September 2023 to March 2024. For this analysis all credits that defaulted before October 2023 were eliminated, taking out any other reason for defaulting than the Hurricane Otis effect. It is also notorious how monthly payments decreased, or default increased the same month Hurricane Otis hit Acapulco (Graph 2). Hurricane Otis policies were installed in November 2023 and were also discussed in the introduction section of this paper.

The hypothesis posits that commitment leads directly to cooperative behavior which is vital for long-term mutually beneficial relationships. This hypothesis is grounded in the premise that if the lender commits to the borrower the second will be loyal and respond

[3] Groups consist of on average 10 female entrepreneurs that follow the group lending business model.
[4] Based on an exchange rate of 17.5 MXP/USD.

positively to payment requirements. By increasing the probability of payment, the borrower (survival entrepreneur) will reflect a commitment to the lender (MFI) when the second shows support to the first in difficult times and financial distress.

Logistic regression was chosen due to the binary outcome variable (Payment/No Payment). This method estimates the probability of repayment while accounting for nonlinear relationships between predictors (Support, LNIntRate, CapEx) and the outcome. Credits defaulting before COVID-19/Otis timelines were removed to isolate crisis effects. Interest rates and expected capital (CapExp) were included to reduce confounding. Tested delayed effects (0/1/2-month lags) to address temporal bias in post-disaster recovery.

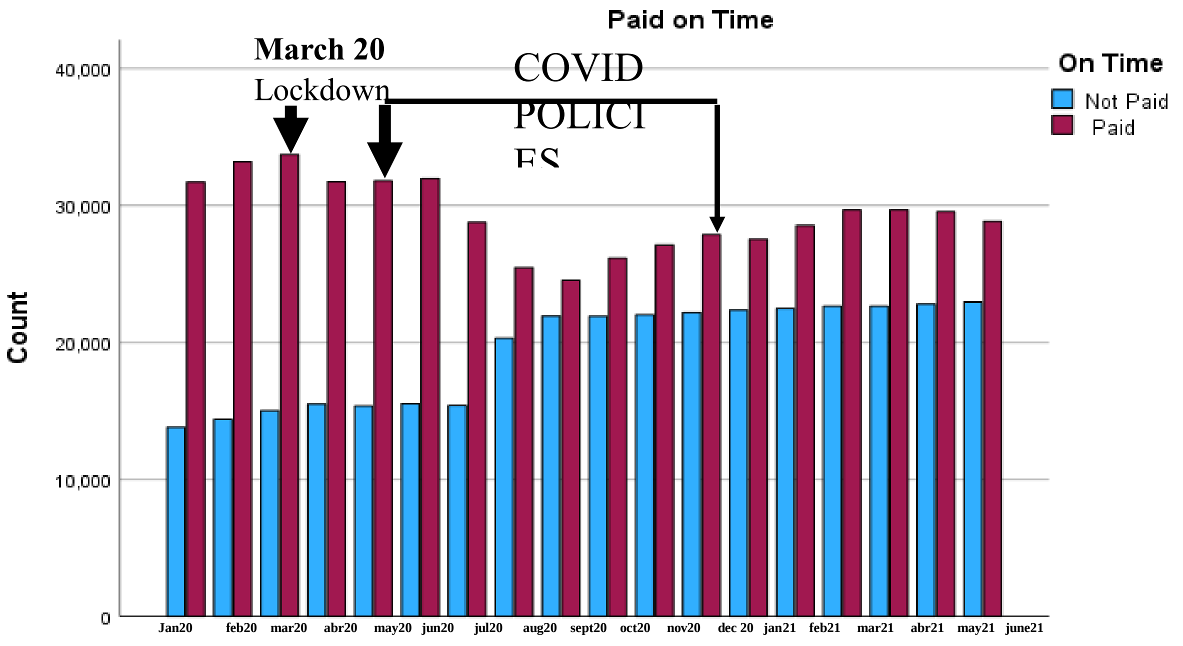
Logit regressions are used in this study due to the binary nature of the dependent variable, which represents whether a specific outcome occurs (e.g., Support of MFI to Survival Entrepreneur vs. no support and Payment of the Survival Entrepreneur vs. no Payment). Logit regressions are particularly suitable for modeling dichotomous outcomes, as they estimate the probability of an event occurring based on predictor variables. This method provides a robust framework for understanding the influence of multiple independent variables on a categorical dependent variable, allowing for the interpretation of odds ratios and the assessment of the relative impact of each predictor. Furthermore, logit regressions accommodate non-linear relationships between the dependent and independent variables, ensuring a more accurate and meaningful analysis of the data. SPSS was used to process all data.

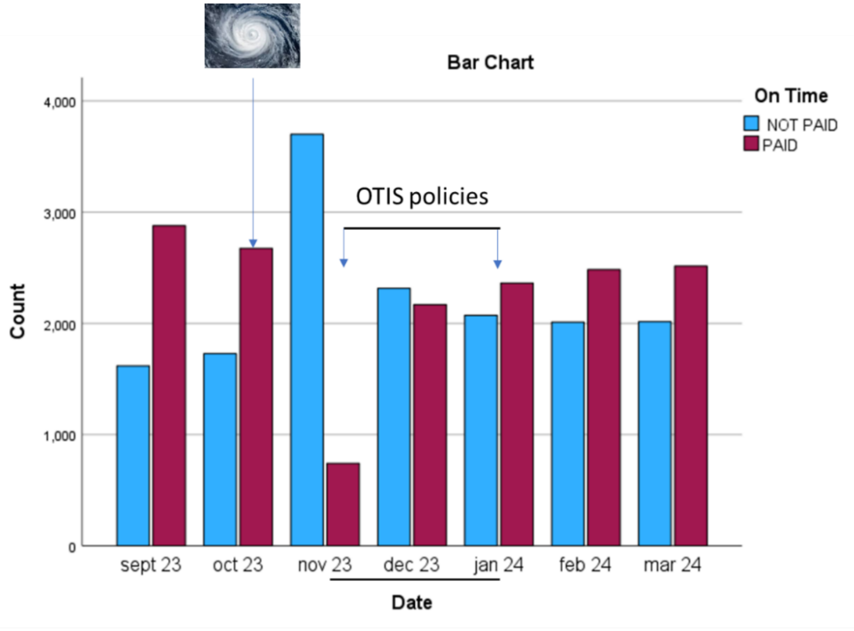
After proving different logit regressions with different independent variables, and checking for normality, heteroscedasticity, and multicollinearity the following regression was used to test the hypothesis:

$$P(Payment = 1, Default = 0) = \beta 0 + \beta 1 Support(Support = 1,\ no\ Support = 0) + \beta 2 LNIntRate + \beta 3 CapEx + \epsilon$$

The dependent variable is Payment (1=Paid, 0=Not Paid). Paid means that the borrower paid the credit on time. Not Paid meaning borrower defaulted and failed to pay the exact day. One day of delay is considered Not Paid.

The independent variables are *Support*, *LNIntRate*, and *CapEx*. *Support*, meaning that the borrower received the benefits of the policies in the financial distress months. This is the variable of interest that proves or rejects the hypothesis. *LNIntRate* is used as a control variable, meaning the natural log of the current yearly interest rate of the loan. Finally, *CapEx*, is another control variable, meaning the capital the MFI (lender) expects to receive from the survival entrepreneur (borrower). In other words, the debt of the borrower at the time. And last, ϵ, stands for the error that represents the difference between the observed value and the value predicted by the regression model.





likelihood of *Support*. Specifically, reducing credit demands during difficult times and providing support to struggling entrepreneurs significantly increases the odds of payment. This hypothesis was confirmed for both the COVID-19 and Hurricane Otis scenarios. However, the timing of payment responses differed between the two events. During COVID-19, the response to payment was immediate, whereas, for Hurricane Otis, there was a two-month lag before entrepreneurs began repaying their credit and interest. For the analysis, the logistic regression was conducted using lag periods of 0, 1, and 2 months. This approach examined the payment behavior immediately (lag 0), one month later (lag 1), and two months later (lag 2) after the microfinance institution (MFI) started supporting the entrepreneurs by relaxing credit policies.

$$P(Payment = 1, Default = 0) = \beta 0 + \beta 1 Support(Support = 1, no\ Support = 0) + \beta 2 LNIntRate + \beta 3 CapEx + \epsilon$$

Logistic Regression ***(****COVID-19 LAG 0)*

The constant in the logistic regression analysis at Step 0 (Table 1) has a coefficient (B) of 0.312, a standard error (S.E.) of 0.002, a Wald statistic of 16275.354, and a very significant p-value (< 0.001). This is the only constant included in the model. The constant's odds ratio (Exp(B)) is 1.366, meaning that the baseline probabilities of the event occurring in the absence of any predictor variables are 1.366. This implies that the probability of the result is already slightly higher, even in the absence of any particular predictors. The strong explanatory power of the utilized predictors is indicated by the goodness-of-fit metrics of the logistic regression model. The model's match to the observed data is indicated by the -2 Log Likelihood value of 387801.699; lower values, however, reflect a better fit. Though without comparison to other models, a number by itself doesn't offer a comprehensive evaluation, lower values suggest a better fit (Table 2). A significant but incomplete explanatory power is indicated by the Cox & Snell R Square value of 0.550, which indicates that the model accounts for 55% of the variance in the dependent variable. Moreover, the Cox & Snell measure is adjusted by the Nagelkerke R Square value of 0.739 to yield a more readable result, indicating that the model accounts for roughly 73.9% of the variation in the result. This high number provides confidence in the model's predictive abilities and possible real-world applications by highlighting the predictors' efficacy and indicating a significant link between the independent and dependent variables.

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 0	Constant	.312	.002	16275.354	1	<.001	1.366

Table 1

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	387801.699[a]	.550	.739

Table 2

Step 1's logistic regression analysis (Table 3) identifies a number of important determinants of the outcome's likelihood. The regression coefficient (β) for the variable "Support" is 0.139, and its standard error is 0.008, resulting in a Wald statistic of 275.999 and a p-value of less than 0.001.

With an odds ratio of 1.149, this shows a positive correlation between "Support" and the probability of the desired event, "Payment." This means that for every unit rise in "Support," the odds of "Payment" increase by around 14.9%.

The Wald statistic for the variable "LNinterest" is 10872.477, with a p-value of less than 0.001, and a regression coefficient of -2.207 with a standard error of 0.021. The inverse relationship between "LNinterest" and the likelihood is indicated by this negative coefficient of "Payment," with a 0.110 odds ratio. Consequently, the likelihood of "Payment" is reduced by 89% for every unit increase in "LNinterest".

Regression coefficient of -3.016 and standard error of 0.008 for the variable "CapEx" result in a Wald statistic of 130912.993 and a p-value of less than 0.001. The odds of "Payment" are decreased by 95.1% for every unit rise in "CapEx" due to this negative connection, which has an odds ratio of 0.049.

Finally, the constant term has an extraordinarily high odds ratio of 339950.864, a regression coefficient of 12.737, a standard error of 0.103, a Wald statistic of 15296.148, and a p-value of less than 0.001. The baseline log chances of "Payment" when all predictors are 0 are shown by this high constant value.

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	Support	.139	.008	275.999	1	<.001	1.149
	LNinterest	-2.207	.021	10872.477	1	<.001	.110
	CapEx	-3.016	.008	130912.993	1	<.001	.049
	Constant	12.737	.103	15296.148	1	<.001	339950.864

a. Variable(s) entered on step 1: Support, LNinterest, CapEx.

Table 3

Logistic Regression COVID-19 LAG 1

The constant has a coefficient (B) of 0.282 and a standard error (S.E.) of 0.003 in the logistic regression analysis at Step 0 (Table 4), where the constant is the only component of the model. The constant is extremely statistically significant, as indicated by the Wald statistic of 12502.647 and the p-value of less than 0.001. The constant's odds ratio (Exp(B)) is 1.326, indicating that the baseline probabilities of the event occurring in the absence of any predictor variables are 1.326. This means that there is already a moderate chance of the event happening even if no particular predictors are taken into account.

A -2 Log Likelihood value of 366371.098 is shown by the logistic regression analysis at Step 1 (Table 5), demonstrating how well the model fits the observed data. With a Cox & Snell R Square of 0.548, the model has a significant amount of explanatory power, explaining roughly 54.8% of the variance in the dependent variable. This measure's Nagelkerke R Square value of 0.735 brings it down to a more readable scale, showing that the model accounts for around 73.5% of the variation in the result. This high number demonstrates the model's excellent predictive power. The parameter estimates stabilized, moving by less than 0.001, indicating convergence and reliability in the model's parameter estimations, and the estimating process was stopped at the ninth iteration.

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 0	Constant	.282	.003	12502.647	1	<.001	1.326

Table 4

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	366371.098a	.548	.735

a. Estimation terminated at iteration number 9 because parameter estimates changed by less than .001.

Table 5

Multiple significant predictors of the dependent variable are identified by the Step 1 logistic regression analysis (Table 6). The Wald statistic for the variable "Support" is 375.420, with a p-value of less than 0.001, and a coefficient (B) of 0.166 with a standard error (S.E.) of 0.009. With an odds ratio (Exp(B)) = 1.181, this suggests a positive and statistically significant relationship between "Support" and the probability of "Payment." This indicates that the probability of the "Payment" rises by 18.1% for every unit increase in "Support".

The dependent variable has multiple significant predictors, as shown by the Step 1 logistic regression analysis (Table 6). A Wald statistic of 375.420 and a p-value of less than 0.001 are produced by the variable "Support" with a coefficient (B) of 0.166 and a standard error (S.E.) of 0.009. This shows that "Support" and the chance of "Payment" are positively and statistically significantly correlated, with an odds ratio (Exp(B)) of 1.181. Accordingly, the chances of the "Payment" rises by 18.1% for every unit increase in "Support".

The Wald statistic for the variable "LNinterest" is 10408.639, with a p-value of less than 0.001, and a negative coefficient of -2.215 with a standard error of 0.022. According to this strong negative connection (odds ratio of 0.109), the chances of "Payment" drop by 89.1% for every unit increase in "LNinterest".

The Wald statistic for "CapEx" is 122724.542, with a p-value of less than 0.001, and it has a negative coefficient of -2.951 with a standard error of 0.008 as well. With an odds ratio of 0.052, it can be inferred that a unit increase in "CapEx" results in a 94.8% decrease in the likelihood of "Payment."

The constant term has an extraordinarily high odds ratio of 334507.477, a Wald statistic of 14489.878, a p-value of less than 0.001, and a coefficient of 12.720 with a standard error of 0.106. When all predictors are zero, this suggests a high baseline log-odds of

"Payment." In summary, the findings underscore the noteworthy influence of "Support," "LNinterest," and "CapEx" on the probability of "Payment," underscoring their significance within the framework.

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1a	Support	.166	.009	375.420	1	<.001	1.181
	LNinterest	-2.215	.022	10408.639	1	<.001	.109
	CapEx	-2.951	.008	122724.542	1	<.001	.052
	Constant	12.720	.106	14489.878	1	<.001	334507.477

a. Variable(s) entered on step 1: Support, LNinterest, CapEx.

Table 6

Logistic Regression COVID LAG 2

Understanding of the dependent variable's predictors is possible thanks to the logistic regression analysis. The constant has a coefficient (B) of 0.251, a standard error (S.E.) of 0.003, and a Wald statistic of 9197.676, which is highly significant ($p < 0.001$) when there are no predictors in the model Step 0 (Table 7). The constant's odds ratio (Exp(B)) is 1.285, which represents the "Payment" baseline odds.

Several predictors were included in the final model Step 1 (Table 8): "Support," "LNinterest," and "CapEx." The value of -2 Log Likelihood dropped to 345156.603, suggesting a better match for the model. Strong explanatory power is demonstrated by the model's ability to explain between 54.6% and 73.1% of the variance in the dependent variable, as indicated by the Cox & Snell R Square value of 0.546 and the Nagelkerke R Square value of 0.731. The parameter estimates changed by less than 0.001, suggesting convergence, and the estimating procedure was stopped at the ninth iteration.

A number of factors were included in the final model Step 1 (Table 8): "Support," "LNinterest," and "CapEx." A better model fit is indicated by the -2 Log Likelihood value dropping to 345156.603. The model has excellent explanatory power, as evidenced by the Cox & Snell R Square value of 0.546 and the Nagelkerke R Square value of 0.731, which indicate that it explains 54.6% to 73.1% of the variance in the dependent variable. At the ninth iteration, the estimation process was stopped because the parameter estimations showed convergence with changes of less than 0.001.

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 0	Constant	.251	.003	9197.676	1	<.001	1.285

Table 7

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	345156.603[a]	.546	.731

a. Estimation terminated at iteration number 9 because parameter estimates changed by less than .001.

Table 8

In the case of "Support," the coefficient is 0.137, the Wald statistic is 240.939, the standard error is 0.009, and the p-value is very significant (< 0.001). Based on Table 9, the chances ratio of 1.147 indicates that a unit increase in "Support" corresponds to a 14.7% rise in the probabilities of "Payment."

The Wald statistic for "LNinterest" is 9872.935, the coefficient is -2.214 with a standard error of 0.022, and the p-value is less than 0.001. With an odds ratio of 0.109, the chances of "Payment" are reduced by 89.1% for every unit rise in "LNinterest".

"CapEx" has a coefficient of -2.881, a standard error of 0.009, a Wald statistic of 114453.024, and a p-value of less than 0.001. The odds ratio of 0.056 suggests that each unit increase in "CapEx" reduces the odds of “Payment” by 94.4%.

With an odds ratio of 326448.383, a Wald statistic of 13701.365, a p-value of less than 0.001, and a constant term of 12.696, the final model has a standard error of 0.108. The baseline log chances of "Payment" when all predictors are 0 are reflected in this high value. These findings demonstrate how important "Support," "LNinterest," and "CapEx" are in predicting "Payment," with each factor having a major influence on the chance of "Payment."

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	Support	.137	.009	240.939	1	<.001	1.147
	LNinterest	-2.214	.022	9872.935	1	<.001	.109
	CapEx	-2.881	.009	114453.024	1	<.001	.056
	Constant	12.696	.108	13701.365	1	<.001	326448.383

a. Variable(s) entered on step 1: Support, LNinterest, CapEx.

Table 9

Logistic Regression OTIS LAG 0

With just the constant in the model, the logistic regression analysis at Step 0 (Table 10) yields a highly significant p-value (< 0.001), a coefficient (B) of -0.165, a standard error (S.E.) of 0.013, and a Wald statistic of 151.564. The constant's odds ratio (Exp(B)) is 0.848, which represents the "Payment" baseline odds.

Several predictors were included in the final model Step 1 (Table 11): "Support," "LnInt," and "CapEx." With a -2 Log Likelihood value of 6589.894, the model is well-fitted. Strong explanatory power is demonstrated by the model's ability to explain between 66.2% and 88.5% of the variation in the dependent variable, as indicated by the Cox & Snell R Square value of 0.662 and the Nagelkerke R Square value of 0.885. When parameter estimations stabilized and changed by less than 0.001, the estimating procedure came to an end at the tenth iteration.

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 0	Constant	-.165	.013	151.564	1	<.001	.848

Table 10

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	6589.894[a]	.662	.885

a. Estimation terminated at iteration number 10 because parameter estimates changed by less than .001.

Table 11

The variable "Support" by its coefficient of -0.151, standard error of 0.068, Wald statistic of 4.922, and p-value of 0.027, indicates the significant relationship to “Payment” . According to the odds ratio of 0.860, there is a 14% drop in the likelihood of "Payment" for every unit increase in "Support".

With a coefficient of -1.549, a standard error of 0.164, a Wald statistic of 89.032, and a p-value of less than 0.001, "LnInt" (log-transformed interest) is analyzed. With an odds ratio of 0.212, the chances of "Payment" are reduced by 78.8% for every unit increase in "LnInt".

The data for "CapExp" (expected capital) show a coefficient of -0.497, a standard error of 0.008, a Wald statistic of 3416.061, and a p-value less than 0.001. According to the odds ratio of 0.609, there is a 39.1% decrease in the likelihood of "Payment" for every unit rise in "CapExp".

The resulting model's constant term has an odds ratio of 32121.658, a coefficient of 10.377, a standard error of 0.798, a Wald statistic of 169.103, and a p-value of less than 0.001. The baseline log chances of "Payment" when all predictors are 0 are indicated by this high number. The findings indicate that "Support," "LnInt," and "CapExp" have a noteworthy influence on the probability of "Payment," with each predictor having a large impact on the odds of "Payment."

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	Support	-.151	.068	4.922	1	.027	.860
	LnInt	-1.549	.164	89.032	1	<.001	.212
	CapExp	-.497	.008	3416.061	1	<.001	.609
	Constant	10.377	.798	169.103	1	<.001	32121.658

a. Variable(s) entered on step 1: Support, LnInt, CapEx.

Table 12

Logistic Regression OTIS LAG 1

The logistic regression analysis begins with the constant-only model Step 0 (Table 13), where the constant has a coefficient (B) of 0.124, a standard error (S.E.) of 0.015, a Wald statistic of 69.198, and a highly significant p-value (< 0.001). The odds ratio (Exp(B)) for the constant is 1.133, indicating the baseline odds of "Payment".

In the final model Step 1 (Table 14), three predictors are included: "Support," "LnInt" (log-transformed interest), and "CapEx" (Expected Capital) The -2 Log Likelihood value of 4394.250 suggests a well-fitting model. The Cox & Snell R Square value of 0.679 and the Nagelkerke R Square value of 0.907 indicate that the model explains between 67.9% and 90.7% of the variance in the dependent variable, demonstrating very strong explanatory power. The estimation process was terminated at the tenth iteration as parameter estimates changed by less than 0.001, indicating convergence.

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 0	Constant	.124	.015	69.198	1	<.001	1.133

Table 13

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	4394.250[a]	.679	.907

a. Estimation terminated at iteration number 10 because parameter estimates changed by less than .001.

Table 14

For "Support," the coefficient is 0.115, with a standard error of 0.085, a Wald statistic of 1.847, and a p-value of 0.174. This indicates that "Support" is not a statistically significant predictor of "Payment" at the 0.05 level. The odds ratio of 1.122 suggests a 12.2% increase in the odds of "Payment" per unit increase in "Support," but this result is not statistically significant (Table 15).

"LnInt" has a coefficient of -1.323, a standard error of 0.204, a Wald statistic of 42.182, and a p-value of less than 0.001, indicating a significant negative relationship with “Payment”. The odds ratio of 0.266 suggests that each unit increase in "LnInt" decreases the odds of “Payment” by 73.4%.

"CapEx" has a coefficient of -0.619, a standard error of 0.012, a Wald statistic of 2500.214, and a p-value of less than 0.001, showing a significant negative association with “Payment”. The odds ratio of 0.538 indicates that each unit increase in "CapEx" reduces the odds of “Payment” by 46.2%.

The constant term in the final model has a coefficient of 9.585, a standard error of 0.988, a Wald statistic of 94.057, and a p-value of less than 0.001, with an odds ratio of 14541.639. This high value indicates the baseline log odds of “Payment” when all predictors are zero. Overall, these results highlight the significant impact of "LnInt" and "CapEx" on the likelihood of “Payment”, while "Support" does not have a statistically significant effect in this model.

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	Support	.115	.085	1.847	1	.174	1.122
	LnInt	-1.323	.204	42.182	1	<.001	.266
	CapEx	-.619	.012	2500.214	1	<.001	.538
	Constant	9.585	.988	94.057	1	<.001	14541.639

a. Variable(s) entered on step 1: Support, LnInt, CapEx.

Table 15

Logistic Regression OTIS LAG 2

The logistic regression analysis begins with the constant-only model Step 0 (Table 16), where the constant has a coefficient (B) of 0.188, a standard error (S.E.) of 0.017, a Wald statistic of 117.798, and a highly significant p-value (< 0.001). The odds ratio (Exp(B)) for the constant is 1.207, indicating the baseline odds of “Payment”.

In the final model Step 1 (Table 17), which includes the predictors "Support," "LnInt" (log-transformed interest), and "CapEx" (expected capital), the -2 Log Likelihood value is 3604.524, suggesting a good fit. The Cox & Snell R Square value of 0.670 and the Nagelkerke R Square value of 0.896 indicate that the model explains between 67.0% and 89.6% of the variance in the dependent variable, demonstrating very strong explanatory power. The estimation process terminated at the ninth iteration as parameter estimates changed by less than 0.001, indicating convergence.

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 0	Constant	.188	.017	117.798	1	<.001	1.207

Table 16

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	3604.524[a]	.670	.896

a. Estimation terminated at iteration number 9 because parameter estimates changed by less than .001.

Table 17

For "Support," the coefficient is 0.315, with a standard error of 0.101, a Wald statistic of 9.754, and a p-value of 0.002, indicating statistical significance. The odds ratio of 1.371 suggests that each unit increase in "Support" increases the odds of “Payment” by 37.1% (Table 18).

"LnInt" has a coefficient of -1.403, a standard error of 0.224, a Wald statistic of 39.233, and a p-value of less than 0.001, indicating a significant negative relationship with “Payment”. The odds ratio of 0.246 suggests that each unit increase in "LnInt" decreases the odds of “Payment” by 75.4%.

"CapEx" has a coefficient of -0.577, a standard error of 0.013, a Wald statistic of 2011.336, and a p-value of less than 0.001, showing a significant negative association with “Payment”. The odds ratio of 0.561 indicates that each unit increase in "CapEx" reduces the odds of “Payment” by 43.9%.

The constant term in the final model has a coefficient of 9.874, a standard error of 1.087, a Wald statistic of 82.498, and a p-value of less than 0.001, with an odds ratio of 19411.417. This high value indicates the baseline log odds of “Payment” when all predictors are zero. Overall, these results highlight the significant impact of "Support," "LnInt," and "CapEx" on the likelihood of “Payment”, with "Support" increasing the odds and both "LnInt" and "CapEx" decreasing the odds of “Payment”.

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	Support	.315	.101	9.754	1	.002	1.371
	LnInt	-1.403	.224	39.233	1	<.001	.246
	CapEx	-.577	.013	2011.336	1	<.001	.561
	Constant	9.874	1.087	82.498	1	<.001	19411.417

a. Variable(s) entered on step 1: Support, LnInt, CapEx.

Table 18

ODDS

Event	Lag 0	1	2
COVID-19	14.9%**	18.1%**	14.7%**
HURRICANE OTIS	(14%)**	12.20%	37.1%**

**Sig. <.001

Table 19

Conclusions, implications and further research

Commitment from the MFI to the financially distressed entrepreneur pays off as the probability of payment increases. Loyalty is presumably generated when commitment is exerted from the MFI to entrepreneurs in a situation of financial distress.

For COVID-19, the effects of increasing the probability of payment are immediate. Lag 0, 1, and 2 present commitments from the survival entrepreneur as support is given in financially distressed times (Table 19). For Hurricane Otis, the effects of increasing the probability of payment have been delayed. Note that in Lag 0, still support has even a negative effect on the probability of payment of a negative 14%. In Lag 1, the odds increase to 12.20% but with no significance. It is until Lag 2 that we see the effects of support with a winner 37.1% increase in the probability of payment.

The reasons for this difference allow further research. Is it the intensity of the financial distress (caused by the event) that caused the delay in the effects of "Support" on "Payment"? Why does the probability of payment in Lag 2 surpass the rest of the probabilities? Is the nature of the event related to the differences in the effects of "Support" on "Payment"?

The future of this line of research is fascinating as climate change, political turmoil, conflicts among countries, affecting the economic environment affecting survival entrepreneurs and suppliers of funds. More collaboration is needed between both economic agents. Commitment in the relationship might be the key to navigating in these uncertain times.

A managerial implication of the current findings is that MFIs should adopt flexible repayment policies during crises to build long-term borrower loyalty. Interest rate caps could further enhance repayment rates. A theoretical implication is to extend relationship lending literature by integrating commitment dynamics during exogenous shocks. It also validates resource dependence theory in microfinance contexts. And a social implication suggests strengthening financial inclusion for marginalized groups, reducing poverty cycles through crisis-responsive lending.

This study advances microfinance research by quantifying how MFI-emergency support fosters borrower commitment during crises. Using dual disaster datasets (COVID-

19/Otis), it reveals temporal differences in repayment behavior, emphasizing the role of adaptive policies. Theoretically, it bridges organizational stress and entrepreneurial economics, offering a framework for resilience in informal economies. Practically, it demonstrates that short-term flexibility yields long-term reciprocity, enhancing MFI sustainability and social impact.

References

Armendáriz, B., & Morduch, J. (2010). The Economics of Microfinance. MIT Press.

Bateman, M. (2010). Why Doesn't Microfinance Work? The Destructive Rise of Local Neoliberalism. Zed Books.

Beck, T., Demirgüç-Kunt, A., & Maksimovic, V. (2008). Financing Patterns Around the World: Are Small Firms Different? Journal of Financial Economics, 89(3), 467-487.

Berg, T., Burg, V., Gombović, A., & Puri, M. (2020). On the Rise of FinTechs – Credit Scoring Using Digital Footprints. The Review of Financial Studies, 33(7), 2845-2897.

Berger, A. N., & Udell, G. F. (1995). Relationship Lending and Lines of Credit in Small Firm Finance. Journal of Business, 68(3), 351-381.

Boot, A. W. A. (2000). Relationship Banking: What Do We Know? Journal of Financial Intermediation, 9(1), 7-25.

Cole, R. A. (1998). The Importance of Relationships to the Availability of Credit. Journal of Banking & Finance, 22(6-8), 959-977.

Cull, R., Demirgüç-Kunt, A., & Morduch, J. (2009). Microfinance meets the market. Journal of Economic Perspectives, 23(1), 167-192.

Degryse, H., & Van Cayseele, P. (2000). Relationship Lending within a Bank-Based System: Evidence from European Small Business Data. Journal of Financial Intermediation, 9(1), 90-109.

Elsas, R., & Krahnen, J. P. (1998). Is Relationship Lending Special? Evidence from Credit-File Data in Germany. Journal of Banking & Finance, 22(10-11), 1283-1316.

Fernando A. Moya Dávila, (2019). "Relationship Lending and Entrepreneurial Behavior: Analyzing Empirical Evidence," Springer Books, in Rajagopal & Ramesh Behl (ed.), Business Governance and Society, chapter 0, pages 321-347, Springer.

Fernando A. Moya-Dávila & Ananya Rajagopal, (2020). "Managing Microfinance Institutions: Analyzing How Relationships Influence Entrepreneurial Behavior," Springer Books, in Rajagopal & Ramesh Behl (ed.), Innovation, Technology, and Market Ecosystems, chapter 0, pages 85-107, Springer.

Fernando A. Moya-Dávila (2018). Relationship Lending and Entrepreneurial Behavior: A Game-Theoretic-Based Modeling. 10.4018/978-1-5225-4831-7.ch006.

Gabay-Mariani, L., Bastian, B., Caputo, A. and Pappas, N. (2024), "Hidden stories and the dark side of entrepreneurial commitment", International Journal of Entrepreneurial Behavior & Research, Vol. 30 No. 6, pp. 1553-1575. https://doi.org/10.1108/IJEBR-03-2023-0248

Ghosh, R., & Guha, S. (2014). Use of Technology in Microfinance. Journal of South Asian Development, 9(2), 153-173.

Guérin, I., Morvant-Roux, S., & Villarreal, M. (2014). Microfinance, Debt and Over-Indebtedness: Juggling with Money. Routledge.

Hansen, K. T., Little, W. E., & Milgram, B. L. (Eds.). (2014). *Street economies in the urban global South*. School for Advanced Research Advanced Seminar Series.

Hermes, N., & Lensink, R. (2011). Microfinance: Its impact, outreach, and sustainability. World Development, 39(6), 875-881.

Hofstede, G. (1980). Culture's Consequences: International Differences in Work-Related Values. Sage Publications.

Jaros, S. J. (1997). An assessment of Meyer and Allen's (1991) three-component model of organizational commitment and turnover intentions. Journal of Vocational Behavior, 51(3), 319-337.

Johnson, M. P. (1991). Commitment to personal relationships. In W. H. Jones & D. Perlman (Eds.), Advances in Personal Relationships (Vol. 3, pp. 117-143). Jessica Kingsley Publishers.

Khandker, S. R. (2005). Microfinance and poverty: Evidence using panel data from Bangladesh. The World Bank Economic Review, 19(2), 263-286.

Lehmann, E., & Neuberger, D. (2001). Do Lending Relationships Matter? Evidence from Bank Survey Data in Germany. Journal of Economic Behavior & Organization, 45(4), 339-359.

Meyer, J. P., & Allen, N. J. (1991). A three-component conceptualization of organizational commitment. Human Resource Management Review, 1(1), 61-89.

Meyer, J. P., Allen, N. J., & Smith, C. A. (1993). Commitment to organizations and occupations: Extension and test of a three-component conceptualization. Journal of Applied Psychology, 78(4), 538.

Meyer, J. P., Stanley, D. J., Herscovitch, L., & Topolnytsky, L. (2002). Affective, continuance, and normative commitment to the organization: A meta-analysis of antecedents, correlates, and consequences. Journal of Vocational Behavior, 61(1), 20-52.

Meyer, J. P., Vandenberghe, C., & Becker, T. E. (2012). Employee commitment and motivation: A conceptual analysis and integrative model. Journal of Applied Psychology, 97(3), 480.

Mowday, R. T., Steers, R. M., & Porter, L. W. (1979). The measurement of organizational commitment. Journal of Vocational Behavior, 14(2), 224-247.

Petersen, M. A., & Rajan, R. G. (1994). The Benefits of Lending Relationships: Evidence from Small Business Data. Journal of Finance, 49(1), 3-37.

Pitt, M. M., & Khandker, S. R. (1998). The impact of group-based credit programs on poor households in Bangladesh: Does the gender of participants matter? Journal of Political Economy, 106(5), 958-996.

Purvanova, R. K., & Bono, J. E. (2009). Transformational leadership in context: Face-to-face and virtual teams. The Leadership Quarterly, 20(3), 343-357.

Rajan, R. G. (1992). Insiders and Outsiders: The Choice between Informed and Arm's-Length Debt. Journal of Finance, 47(4), 1367-1400.

Rhyne, E., & Otero, M. (2006). Microfinance Through the Next Decade: Visioning the Who, What, Where, When and How. ACCION International.

Rusbult, C. E. (1980). Commitment and satisfaction in romantic associations: A test of the investment model. Journal of Experimental Social Psychology, 16(2), 172-186.

Rusbult, C. E., Martz, J. M. (1995). Remaining in an abusive relationship: An investment model analysis of nonvoluntary dependence. Personality and Social Psychology Bulletin, 21(6), 558-571.

Rusbult, C. E., Olsen, N., Davis, J. L., & Hannon, P. A. (2001). Commitment and relationship maintenance mechanisms. In J. Harvey & A. Wenzel (Eds.), Close romantic relationships: Maintenance and enhancement (pp. 87-113). Lawrence Erlbaum Associates.

Sharpe, S. A. (1990). Asymmetric Information, Bank Lending, and Implicit Contracts: A Stylized Model of Customer Relationships. Journal of Finance, 45(4), 1069-1087.

Stafford, L. (2010). Geographic distance and communication during courtship. Communication Research, 37(2), 275-297.

Yunus, M. (1999). *Banker to the poor: Micro-lending and the battle against world poverty*. PublicAffair.