INVESTIGATING THE ROLE OF MICROCREDIT SERVICE IN CASE OF DISASTER IN AN INFORMAL SETTLEMENT USING AGENT BASED MODELLING

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ABSTRACT

Informal settlements in urban areas are frequently exposed to the devastating impacts of climate change and natural hazards due to limited access to essential services and infrastructure. Moreover, they are usually located in environmentally sensitive areas which makes them more vulnerable. Microcredit services, in such a scenario, are proven useful in income generation and asset accumulation according to many researchers. Moreover, its intervention of providing relief funds and restructuring the repayment period in case of disasters is also studied. However, there are not many studies that directly discuss a bottom-up approach, i.e. the decisions and behaviour of households and the functioning of microfinance institutes collectively. As these factors can be effectively modelled using Agent-Based Modelling (ABM), this study aims to investigate the role of microcredit service and its intervention in case of disasters in an informal settlement using Agent-Based Modelling (ABM). The results of the developed ABM provide insight on understanding the process of microcredit service and usefulness of intervention of relief funds in case of disasters. The model suggests that microcredit service along with the intervention of relief fund and restructuring the repayment period is useful in case of disasters. Altogether, the developed model, being the first attempt in modelling an informal settlement in the context of microcredit and disaster, paves the way for the development of more realistic and empirical models in this context.

Keywords: Microcredit, disasters, Agent-Based Modelling (ABM), informal settlements

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1. INTRODUCTION

Rapid urbanisation is one of the most significant challenges faced by developing countries throughout the world. According to the United Nations (UN), almost all the increase in the world's population by 2050 will be in the urban centres of developing nations (IPCC, 2014). This rapid urban growth has progressively exposed the population as well as the economic assets to the devastating impacts of climate change and natural hazards (Baker, 2012). Undoubtedly, the urban poor and socially disadvantaged groups living in slums are the most vulnerable to natural disasters due to their limited access to essential services and infrastructure (Parvin, Shaw, & Shumi, 2016). Furthermore, in most of the cases, the informal settlements are neglected by the governmental authorities as seen in the case of Mumbai, India (Chatterjee, 2010). Owing to the lack of governmental aid, residents in informal settlements tend to reduce or adapt to the disaster risk in their own ways (Wamsler & Osborne, 2013). This potential of people to reduce or adapt to the risk is often termed as *adaptive capacity* or *coping capacity*. Coping capacity consists of an immediate response to hazards to maintain livelihoods, whereas adaptive capacity refers to anticipatory or reactive changes which amend the livelihoods and reduce long term vulnerability (Smit & Wandel, 2006). These capacities often determine the survival of slum dwellers in case of a disaster. Therefore, it is essential to identify the ways to make these capacities robust to strengthen the disaster risk reduction framework for the urban poor.

1.1. Background

There are three types of mechanisms that help in strengthening the coping and adaptive capacity of slum dwellers; physical, economic, and social (Wamsler & Osborne, 2013). Physical mechanisms constitute of household and infrastructure repairs whereas economic mechanisms aim at increasing the household income and income security along with economic diversification. Social mechanisms include the dependency upon social networks such as family, neighbours, and community in the time of need (Wamsler & Osborne, 2013). Physical coping mechanisms have a limited impact on the risk reduction as the settlements are situated in environmentally sensitive areas such as creeks, stream channels and other flood zones. Moreover, not every household within the slum is able to invest in structural modifications due to low income (Chatterjee, 2010), resulting in the dependence of slum dwellers on economic and social coping mechanisms.

Microfinance, in this situation, has been considered to facilitate adaptation by enhancing the coping and adaptive capacity. Although it serves as an economic and social coping mechanism, it can also be used to improve the physical coping capacity. For example, the savings can be used to build a wall that protects from the flood (Chatterjee, 2010). Several researchers have explained the link between microfinance and disaster risk reduction. For example, Hammill, Matthew, and McCarter (2009) elaborate upon the potential of microfinance for adaptation towards disasters and climate change whereas Parvin et al. (2016) discuss the existing microfinance practices in urban areas that help in disaster risk management. Furthermore, Parvin and Shaw (2014) deliberate upon the role of MFIs-NGOs in disaster risk reduction for a rural area. Additionally, Fenton, Paavola, and Tallontire (2017) have also explained the role of microfinance in enabling better adaptation of livelihoods.

According to Ledgerwood (1999), *microfinance* refers to the provision of financial services such as credit, savings, insurance and payment to low-income clients. Microfinance Institutes (MFIs) are the units that provide products and services, ranging from Community-Based Organisations (CBOs) to formal institutions such as Non-Governmental Organisations (NGOs) and banks. Most common microfinance services include microcredit, micro-savings, and microinsurance services. Microcredit refers to asset building and income diversification that concentrates on lending funds in small amounts and lower interest rates to low-income people so that they can explore their abilities of job creation (Hammill et al., 2009). Microinsurance provides poor people by ensuring them with protection against risks in exchange for regular premium payments. (Müller, Johnson, & Kreuer, 2017). Microdeposit or micro-savings refer to a service that allows a person to deposit a minimum amount in their accounts (Ledgerwood, 1999). As most of the slum dwellers lack a consistent income and their employment is mostly seasonal, they spend their earnings entirely for basic needs. In such a scenario, it is difficult for MFIs to run micro-saving and microinsurance service successfully. Only after a consistent income and employment, the slum dwellers can avail the facility of micro-savings as well as micro-insurance (Ledgerwood, 2013). Therefore, microcredit service is most commonly observed in informal settlements. Thus, the study focuses only on the microcredit service in the context of disaster risk reduction.

1.2. Research Problem

In theory, the provision of microcredit reduces poverty by facilitating income generation and asset accumulation. According to Alamgir, Jabbar, and Islam (2009), total annual income after obtaining a microcredit to set up a small business in the slums of Bangladesh was changed from around 350$ to 600 $ suggesting an increase in annual income levels after the introduction of microcredits. Apart from this, a microcredit service has a potential to aid in recovery in case of stochastic income shocks by facilitating the search of productive activities that generate income for all the seasons (Fenton, Paavola, & Tallontire, 2015). Thus, microcredit service is considered to be valuable in dealing with unexpected disasters.

Adaptation at household level is dependent upon the existing knowledge, resources, credits, and skills. Lack of any of these components might affect the overall resilience of the slum dwellers. However, in many cases, lack of access to credit facilities is identified to be the main problem in recovering from the impact of the disaster (Bryan, Deressa, Gbetibouo, & Ringler, 2009). In such a scenario, microcredit facility not only increases the accessibility to credits but also assists in enhancing the social capital by promoting collective adaptation efforts. For example, the group-based lending mechanisms as introduced by Mohammed Yunus in Bangladesh helped in attaining a certain level of economic stability in the lower income areas (Ledgerwood, 1999). Thus, microcredit facility supports households in coping and recovering from disaster by enhancing the adaptive capacity financially as well as socially.

Microcredit service, although it facilitates adaptation, has been considered to have negative impacts (Hammill et al., 2009). In the study by Fenton et al. (2017), the over-indebtedness of households is one of the negative impacts which refers to an inability to meet repayment deadlines that incurs high costs and increased indebtedness. Sometimes, factors such as high-interest rates and short repayment periods on loans often lead to heavy debts (Dehejia, Montgomery, & Morduch, 2012). Heavy debts increase the stress with an increase in poverty and thus affects the individuals by reducing the overall adaptive capacity. Moreover, an increase in the frequency of hazards also increases the financial dependency of households (Parvin & Shaw, 2013). A new occupation started with credits from MFIs needs time to initiate, and with an increase in the frequency of hazard, more financial help is required in order to manage the losses. To facilitate the residents during disasters, MFIs are often observed to provide emergency funds along with rescheduling of loans (Kumar & Newport, 2005). According to Becchetti and Castriota (2011), provision of emergency loans to the villagers after Tsunami uplifted them in terms of income. Rescheduling of loans has also been effective in 1998 floods of Bangladesh where it led to a significant decrease in the default rate of clients (Naveen Kumar, Manjunath, & H.S., 2012). However, an increase in the frequency of disasters might affect the effectiveness of this intervention along with the process of provision of microcredit. For example, in case of the absence of relief funds with MFI during disasters might lead the residents to the state of indebtedness. Moreover, the residents might repeatedly need these relief funds to restore the developed business from disaster. However, continuous provision of relief funds may possibly affect the liquidity of MFI. Therefore, there is a need to investigate the role of microcredit service along with the interventions such as provision of relief fund and rescheduling of repayment period in case of various frequencies of disasters in an informal settlement.

1.3. Why Agent-Based Model?

As explained above, the characteristics of MFIs such as interest rate, repayment period or the interventions influence the usefulness of the service. However, the conditions and perceptions of the residents in the informal settlement also affect the usefulness of microcredit service in case of disasters (Ahlin, 2015; Mirpourian, Caragliu, Di Maio, Landoni, & Rusinà, 2016; Mokhtar, Nartea, & Gan, 2012). As discussed above, several studies have provided insights on the role of microcredit and intervention of relief fund. However, not many studies directly deliberate upon the factors that are related to the behaviour of households and the functioning of microfinance institutes collectively. As these factors affect the outcome of the microcredit service, it is essential to link the characteristics and behaviour of components like slum dwellers and the MFIs to the system dynamics. Agent-Based Models (ABMs) provide a decentralised and dynamic environment with agents that are unique and autonomous entities that interact with each other and the environment (Railsback & Grimm, 2012). ABMs in this context can aid in simulating the behaviour of households and the strategies of MFIs before the implementation of the service to identify the conditions for its usefulness in case of a disaster in the informal settlement. Therefore, the study attempts explicitly to use ABM in this context.

1.4. Research Objective

To investigate the role of microcredit service and its intervention[1] in case of disasters in an informal settlement using ABM.

1.4.1. Sub-objectives and Research Questions

1. To elaborate upon the components of microcredit service along with characteristics of disasters in an informal settlement.
    a. What are the characteristics of disasters and their impacts on the informal settlement?
    b. What are the characteristics of microcredit services in informal settlements?
    c. How are they affecting the residents and the functioning of MFI in general?
2. To develop a conceptual framework that incorporates the relationship between microcredit services and slum dwellers in case of disasters.
    a. What are the agents (type and number) and their respective attributes?
    b. What are the possible interactions amongst the agents and between agents and the environment?
    c. How and upon what do the agents decide? What are the processes that will feed into the model?
3. To implement the ABM that aids in understanding the effectiveness of microcredit service and respective intervention in enhancing the resilience of residents.
    a. What is the pattern observed after the introduction of microcredit service in an informal settlement?
    b. What is the pattern observed after the intervention of MFI with respect to disaster in an informal settlement?
    c. How is the model output changing with the change in input parameters?
4. To evaluate the performance of the developed model.
    a. Do the model results conform with the existing literature review?
    b. What are the strengths and weaknesses of the model?
    c. What are the possible recommendations to improve the model?

[1] Intervention in this thesis is referred to provision of relief fund and rescheduling of repayment period

1.5. Thesis Structure

The structure of the thesis is as follows:

Chapter 1: Introduction, introduces the study by explaining the need and gap of the study. Moreover, it explains the research objectives along with the sub objectives and research questions.

Chapter 2: Literature Review, explains the two main concepts involved in the thesis; microcredit service and disasters. It also briefly mentions the existing ABMs in the context of this study.

Chapter 3: Methodology, explains the detailed methodology adopted for this research.

Chapter 4: Conceptual framework of the model, explains the conceptual framework of the model using the ODD + D protocol.

Chapter 5: Results of the Model, explains the analysis of the model results in detail.

Chapter 6: Discussion, discusses the results, major outcomes and short comings of the model

Chapter 7: Conclusion, briefly concludes the thesis and provides the scope for future work.

2. LITERATURE REVIEW

This chapter provides an overview of the existing knowledge on microcredit service and its interventions related to disaster risk management. Moreover, it also discusses the perceptions of residents in an informal settlement regarding the microcredit service.

2.1. Disaster Risk Reduction

According to UNISDR (2009), it is essential to understand the characteristics of hazards such as intensity and frequency, exposure and vulnerability, and the evaluation of all the possible adaptive capacities in an area as a prelude to disaster risk reduction. As the study focuses on exploring the role of microcredit service in case of disasters, it is important to understand the concepts of intensity and frequency of hazards along with the exposure and vulnerability of the residents to relate it with disaster risk reduction.

Table 1 defines the concepts that are relevant to disaster risk

Table 1 Definitions

S. N	Term	Definition
1	Disaster	"Serious disruption of the functioning of a community comprising of human, material, economic or environmental losses and impacts, which surpasses the ability of the affected community to cope using its own resources." (UNISDR, 2009, p.09)
2	Hazard	"A dangerous phenomenon, substance, human activity or condition that may cause loss of life, injury or other health impacts, property damage, loss of livelihoods and services, social and economic disruption, or environmental damage." (UNISDR, 2009, p.17)
3	Intensity	The effects observed at a specific location (Jackson, 2013)
4	Frequency	The number of times a hazard occurs in a specified time interval (Westen & Greiving 2017)
5	Vulnerability	"The characteristics and circumstances of a community, system or asset that make it susceptible to the damaging effects of a hazard." (UNISDR, 2009, p. 30)
6	Resilience	"The ability of residents to resist, absorb, accommodate and recover from devastating effects of hazards of hazard in a timely and efficient manner." (Fekete, Hufschmidt, & Kruse, 2014, p.4)
7	Adaptative capacity	"The ability of a system to adjust to climate change (including climate variability and extremes), to moderate potential damages, to take advantage of opportunities, or to cope with the consequences" (Baker, 2012, p. 5)

Disaster Risk can be elucidated as "the potential disaster losses, in lives, health status, livelihoods, assets and services, which could occur to a particular community or a society over some specified future time period" (UNISDR, 2009, p.09-10). Disaster risk depends not only on the intensity and frequency of the hazard but also on the vulnerable conditions that are susceptible to the catastrophic effects of hazard. Disaster risk, therefore, as defined by Wamsler and Osborne (2013), is the probability of a serious disruption which is referred to the interaction between natural hazards (H) and vulnerable conditions (V). This has been therefore equated as follows:

Risk = Hazard x Vulnerability

According to Lei, Wang, Yue, Zhou, and Yin (2014), a hazard is an essential trigger to a disaster, while the level of losses or potential risk is largely determined by the vulnerability and resilience of a system and the type of adaptation measures that are taken. Therefore, the risk is also considered to be a function of vulnerability, resilience and adaptation measures along with the hazards.

In the literature of disaster risk, the term adaptation refers to an action taken in response to actual or expected hazard or their effects that moderates the harm (UNISDR, 2009). Adaptation, therefore, relates to a successful outcome of reducing the overall risk. However, the actions that are taken with intentions of reducing the risk might result in increasing the risk. (Barnett & O'Neill, 2010).

2.2. Vulnerability in Informal Settlement

Informal settlements are a source of affordable housing and economic development in the cities of developing countries. One-third of the urban population i.e. around 863 million people are residing in informal settlements of cities in the world (UN-Habitat, 2012). Informal settlements are located in areas that are exposed to hazards or the areas that are unsuitable for development resulting in increased susceptibility to natural disasters (Gencer, 2013). Furthermore, the households and businesses are also exposed to cascading hazards due to the dilapidated condition and lack of suitable infrastructure (Braun & Aßheuer, 2011). Households in informal settlements tend to have a high vulnerability to disasters mainly because of their low income which further leads to reduced adaptive capacity as well (Rumbach & Shirgaokar, 2017). Therefore, these households, depend significantly upon the savings, small assets and credits or loans offered by informal or formal organisations. Microcredit service has helped in building assets and strengthening income opportunities.

2.3. Microfinance

Microfinance, as mentioned earlier, refers to the provision of financial services such as credit, savings, insurance and payment services to low-income clients. It is a development tool that not only intermediates financially but also provides social intermediation in terms of group formation, development of self-confidence, training in finance and management capabilities (Ledgerwood, 1999). Microfinance, according to Beck (2015), can be defined as an attempt to deliver financial services to low-income, self-employed or informally employed individuals without any formalised ownership title and micro-enterprises that are excluded from traditional commercial banking services. Microfinance can also be termed as delivery of comprehensive financial services such as deposits, loans, payment services, money transfers, and insurance to the poor and low-income households and their microenterprises (Asian Development Bank, 2000). Altogether, microfinance serves as a development tool in uplifting the livelihood of a population with lower income by accumulating and protecting assets and diversifying income opportunities.

2.3.1. Microfinance Institutes (MFIs)

MFIs are the entities that enable provision of these microfinance services. There are many MFIs that are existing in the informal settlements of Asian countries. Few of them are also involved in disaster risk reduction by providing post-disaster credits to households (Parvin et al., 2016). Apart from the financial services, the MFIs also provide training for maintaining accounts and spread awareness regarding disasters. However, such MFIs are not very prevalent (Parvin & Shaw, 2014). Moreover, many of the residents of the informal settlement do not trust the MFIs in terms of microinsurance schemes resulting in smaller outreach of microfinance programmes (Mpanje, Gibbons, & McDermott, 2018). Furthermore, due to frequent hazards and related income shocks, residents find it difficult to repay the loans in stipulated time resulting in heavy debts (Fenton et al., 2017). Besides, the disasters also affect the functioning of MFIs as the demand for credits and loans increases that time. Along with this, the unpaid loans of the residents lead to liquidity problems resulting in the inefficient performance of MFIs in providing an appropriate amount of credits (Parvin et al., 2016).

2.3.2. Microfinance Services

Although the study focuses only on microcredit services, this section intends to explain other services provided by MFIs briefly. As mentioned in the introduction, three main services are provided under microfinance schemes and observed in an informal settlement, that are: microcredit, microinsurance and microdeposit. MFIs often provide these services individually or in combinations of two to three services. Sometimes, these services can be amalgamated with few non-financial services such as health and education as well. It is suggested that the combination of these services lead to better performance of the clients as well as MFIs (Ledgerwood, 2013). For example, premium payments are often linked with loan repayments to achieve high renewals. Sometimes, insurance and savings are also linked in a way that the interest on fixed deposit accounts is used to pay the insurance premiums. However, the challenge is to get the poorest client into this setup (Ledgerwood, 2013). According to Bashar and Rashid (2012), the residents of informal settlements have low savings and assets. Moreover, factors such as trust in the MFIs is not observed in the context of insurance. Many of the residents have a fear of losing their money or not receiving it when in need (Clarke & Grenham, 2013).

2.3.3. Overview of Microcredit Services

There are four main components of microcredit, i.e. amount of loan, repayment period & frequency, interest rate and individual or group loan. These components are said to have an impact on the repayment rate (percentage of people who have repaid the loan successfully) (Pereira & Mourao, 2012). Successful MFIs in the areas such as Bangladesh, Malaysia and India have already witnessed repayment rates above 85% where reasons such as group liability, age and repayment frequencies have played an important role (Pereira & Mourao, 2012).

2.3.3.1. Amount of Loans

The amount of loan depends upon the need in a particular area and funds available with the MFI. Amount of loans can increase over time based on the needs, debt capacity and credit history of the client (Ledgerwood, 2013). Loan sizes are often different for individual and group loans (discussed in section 2.3.5.4). Moreover, based on the credit histories and collaterals of the client the amount of loan is granted by an MFI. This way MFIs verify the credibility of the client to repay the loan. In the studies done so far, the average sizes of the loans are around 125 $ - 800$ depending upon the requirement of the group. The MFIs in places like Morocco and Manila offer around 250$ - 850$ as loans whereas in India, MFIs offer around 125 $ – 1000 $ depending upon the type of loan (individual or group) and depending upon the business idea (Bhole & Ogden, 2010). However, for small businesses the loans required are not more than 350 $ as mentioned in Bashar and Rashid (2012).

2.3.3.2. Repayment Period and Frequency

The repayment period, also termed as loan term, is the length of time the loan is intended to be outstanding (Ledgerwood, 2013). The repayment period associated with loan sizes mentioned above often depend upon the size of the loan and usually vary from a few months to four years (Mirpourian et al., 2016). Shorter repayment periods for a large loan might be a reason for default in repayment of the loan. Moreover, a longer duration of loans that were offered in case of Malaysian MFI TEKUN resulted in borrowers to easily repay the loan (Mokhtar et al., 2012). This means that a longer repayment period, in this case, is a facility for the residents.

Loans are often repaid in equal periodic instalments over the repayment period or at the end as a lump sum depending upon the borrowers' cash flow. The frequency of these instalments is often termed as repayment frequency (Ledgerwood, 2013). It is not just the repayment period that affects repayment. The frequency of repayment has been discussed by many researchers under the domain of repayment and default rate. The repayment frequencies observed are usually weekly, biweekly or monthly throughout the world. Weekly payments were preferred more by the MFIs as it ensures repayment from the clients. In Malaysian MFI TEKUN weekly repayment was not a suitable option because the occupation of residents was mainly agriculture. Thus, it was recommended to have a repayment period according to borrower's revenue cycle. However, the residents involved in small businesses were able to pay the instalments weekly (Mokhtar et al., 2012). E. Field and Pande (2012) did not observe a significant difference in repayment rate when monthly and weekly repayment frequency was compared in the city of Kolkata, India. However, reducing the frequency of repayment is observed to reduce the stress level and improve the performance of residents altogether. Fischer and Ghatak (2010) also emphasize that frequent repayment can reduce welfare by over-borrowing that might occur to pay the existing loans. If the schedule of repayment is made more flexible and designed as per the requirement of the client, it can increase the repayment rate (E. Field & Pande, 2012).

2.3.3.3. Interest rates

The price of credit or loan is termed as the nominal 'interest rate' (Ledgerwood, 2013). The higher operational costs of MFIs lead to higher interest rates on loans (Bashar & Rashid, 2012). The interest rates observed in MFIs of Manila, Hyderabad and Morocco are as low as 11% and 24% per annum. Sometimes the interest rates are increased depending upon the market in that area and to ensure effective repayment from the clients along with the sustainability of MFI (Banerjee, 2013). Residents are often attracted to MFIs with least interest rates and providing loans on larger interest rate might be a cause for reduction in sales of microcredit (Mallick, 2012). Although it appears that clients might be sensitive to interest rates, Dehejia et al. (2012) inform that the changes in interest rate do not affect the clients as the interest rates are often less than those of local moneylenders. Moreover, there is a sense of security with MFIs as they assure more loans with proper repayment of first loans. Interest rates usually fall in between 20% and 50% per year. The most successful example of microcredit lending Grameen Bank Model in Bangladesh provides loans at an interest rate of 20% per annum, and this was considered to be adequate to make the MFI sustainable (Dehejia et al., 2012).

2.3.3.4. Method of interest calculation

Interest is calculated mostly using declining payment method and flat-rate method. Declining balance method calculates interest on the outstanding amount during each loan term whereas the flat-rate method calculates interest on the original disbursed amount (Ledgerwood, 2013). Very few MFIs use declining payment method whereas most of the MFIs use flat-rate method (Bashar & Rashid, 2012). Both the methods have their own positives and drawbacks as explained by Ledgerwood (2013).

2.3.3.5. Group/Individual loans

MFIs provide group and individual loans depending upon their strategy. If the loan size is larger, a group loan is often provided by MFIs. However, a group or individual loan mainly depends upon the collaterals that a resident has to offer to avail the loan. In case of the absence of collateral, the MFI provides loans if a group is formed (Ledgerwood, 2013). Groups usually impose strong social sanctions and introduce peer pressure which persuades people to repay the loans (Bhole & Ogden, 2010).

Borrowers often prefer individual loans if they are wealthier and able to pay loans. It is either a group or an individual loan that dominates the microfinance market in a given country. Lehner (2008) found that most of the MFIs prefer individual loans over group loans when the size of the loan is small, competition is intense and refinancing costs are low. Sometimes, group sizes also affect the successful repayment of the loan. According to Ahlin (2015), an intermediate size of the group does better than any of the extreme group sizes.

2.3.4. Outreach and Sustainability of Microcredit Services

Providing microfinance services has always been a costly affair due to high transaction and information costs (Hermes & Lensink, 2011). Therefore, there has always been a trade-off between outreach and sustainability of microfinance services. The term outreach refers to the provision of financial services to the poorest of the poor and sustainability refers to the covering of total costs by generating enough revenue (Mia & Ben Soltane, 2016). This can be explained using the two approaches (the financial system approach and the poverty lending approach) of MFI services that were debated in the 1990s. The financial system approach focuses more on the importance of covering the costs of lending from the outstanding loan portfolios and reducing the operational costs as much as possible. On the contrary, poverty lending approach stresses on using the credit to eradicate poverty, essentially by providing credit with subsidised interest rates (Robinson & Fidler, 2001). The argument is that the poor cannot afford higher interest rates resulting in deprivation of a large number of poor borrowers from loan facility. Moreover, if the MFIs are not financially sustainable, the outreach cannot be guaranteed in the long-term as well. Therefore, the financial sustainability of MFIs has been given more importance in today's world. However, it has been deliberated by policymakers that the impact of financial sustainability on outreach of microfinance should be carefully analysed (Hermes & Lensink, 2011).

To solve this issue of reducing the transaction and information costs, Wydick, Hayes, and Kempf (2011) suggest that there is an impact of social networks on the outreach of microfinance among the poor. Households may be willing to buy the loans because other households in the network have bought them. Networks bring together the people with similar needs and aims which is why they cooperate under certain circumstances and arrangements (Aßheuer, Thiele-Eich, & Braun, 2013). At micro-level, these networks play an important role not only in sharing information about useful resources such as microfinance but also in combating disasters. As the people with similar level, ethnicity or occupation often stay near to each other, they tend to influence each other's decisions at household level especially related to finances (Gomez & Santor, 2001).

2.3.5. Microfinance in case of Disasters

Informal settlements are extremely diverse and complex suggesting a requirement of in-depth understanding of the entire social and economic context in enhancing the adaptive capacity (Mpanje et al., 2018). According to Parvin and Shaw (2014), a paradigm shift in disaster management from a conventional response and relief practices to an integrated risk reduction by strengthening community coping capacity has led to the incorporation of microfinance in disaster management. Furthermore, it is said that the risk reduction strategies for the poor should aim at reducing economic vulnerability as the financial resilience of the poor helps in reducing the overall vulnerability. In this line, Parvin and Shaw (2013) suggest an approach for the functioning of MFIs that incorporates early warning, infrastructure development, micro-insurance, and risk reduction, response, and recovery considerations.

In rural areas of Asian countries like Bangladesh, the microfinance has enhanced the ability of clients to stabilise their income after a disaster. Most of the people also affirm that with the involvement in microfinance, their awareness regarding disaster recovery has increased. Moreover, longer involvement in microfinance has shown a better adaptive capacity of the people. Despite such positive experiences, many households have not been benefitted from microfinance activities. Instead, the losses are said to be aggravated for a few of them (Parvin & Shaw, 2013). Furthermore, in cases such as reported by Fenton et al. (2017), the individuals often take assistance from microfinance initiatives to repay the loans that are bought from other sources and, thus, fail in establishing the assets and incur tremendous losses.

Similarly, in the context of the urban area, the microfinance has been one of the most appropriate adaptive measures for disaster management. However, as the urban poor face numerous challenges other than income instability that are associated with the housing, water supply, sanitation, health, education and social cohesion, it often becomes difficult for the microfinance schemes to function effectively (Parvin et al., 2016).

There are numerous possibilities of strategic collaboration between microfinance and disaster management and recent studies such as Parvin and Shaw (2013), Fenton et al. (2017) and Hammill et al. (2009) try to understand the role of microfinance on disaster risk reduction. Most of the studies that are done focus on rural areas. Very few studies are observed in the context of the urban poor. However, developing countries like India, Bangladesh and Indonesia are starting to adapt urban microfinancing in disaster management (Parvin et al., 2016). As discussed in the previous section, microcredit service provides relief funds along with the rescheduling of loans to facilitate residents during disasters. In this light, Becchetti and Castriota (2011) suggest that recapitalisation of MFIs under the stress of disasters can act as an expansive monetary policy measure for the poor.

2.4. Existing agent-based models

A study by Rashid, Yoon, and Kashem (2011) is the first attempt to develop an ABM for testing the effects of microcredit. The study incorporated a set of the behaviour of agents such as residents, suppliers of raw materials and MFIs in an economy to test the pre-policy-implementation of microcredit. Based on this model, Bourhime and Tkiouat (2018) compare two types of microcredit services which are Islamic and conventional microfinance and test the impact of Islamic interest-free group loans using the ABM framework. Apart from these stylized models, an empirical model such as Saqalli, Gérard, Bielders, and Defourny (2011) which is based in Nigerian village analysed the impacts of rural development intervention of inventory credit technique and availability of inorganic fertilisers on the population in the village. The developed model was complicated as compared to the previous models and included the behaviour and perception of the population to a larger extent. Few other models such as Barnaud, Bousquet, and Trebuil, (2008) also study the effects of microcredits in rural areas in the context of agriculture and farming. However, it uses Multi-agent systems (MAS) which is similar to ABM. All these studies address the impacts of microcredit using a bottom-up approach. However, in terms of disaster risk, there are no ABMs found in the context of an informal settlement or an urban area that investigate microcredit service in case of disasters. The model developed in this study has been inspired by the ideas and concepts used in these models.

3. RESEARCH METHODOLOGY

The study focuses on modelling microcredit service in an informal settlement with a view to exploring its functionality in case of disaster. Therefore, an approach that allows incorporating the behaviour of agents can enhance the reasoning and aid in understanding the causality of observed impacts. An ABM approach is the most suitable in such a case as it efficiently models a bottom-up process. Moreover, it takes into consideration the behaviour of agents and helps in identification of patterns and processes based on it (Grimm & Railsback, 2005). Furthermore, in impact assessment studies, it is important to build scenarios to understand the impacts in different situations. As ABM allows scenario building with the help of several simulation runs, it is used to undertake this study.

3.1. Purpose and Approach for Modelling

Kelly et al. (2013) suggest that there are mainly five purposes of models; system understanding and hypothesis testing, quantitative predictions, forecasting, management and decision support, communication and learning. The purpose of this model is to understand the system. As abstract, stylized models are easy to understand (Sun et al., 2016), a stylized model is developed in this study that represents a realistic situation of an informal settlement that is frequently affected by hazards. As the model is a stylized model, a simple approach is often suggested. The ABMs are often classified into three types of approaches which are KISS (Keep it Stupid Simple), KIDS (Keep it Descriptive Simple) and KILT (Keep it, Learning Tool). Often the stylized models that do not focus on a specific case study follow KISS approach (Sun et al., 2016). Therefore, the KISS approach is used in developing the ABM for this study.

3.2. Methodology

The methodology is sequenced with respect to the research sub-objectives as shown in Figure 1.

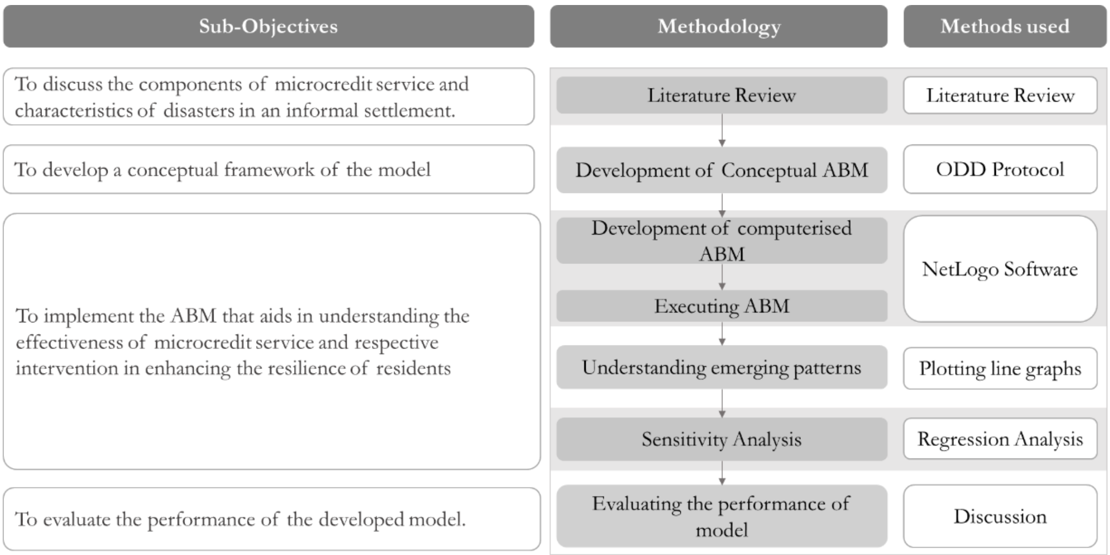


Figure 1 Methodology of the study

3.2.1. Structure of Literature Review

As explained above, as the model is an abstract model that aids in understanding the role of a microcredit service in an informal settlement, a site visit was not a primary requirement of the study. Therefore, to construct a logical model, it was necessary to have a profound literature review that helps in preparing the base of the model. Literature review (see chapter 2), therefore, involved the content on the basics of microcredit service and disaster risk along with the role of microcredit service in case of disasters as discussed by researchers. Moreover, it also discussed the existing ABMs related to the topic.

3.2.2. Development of Conceptual Model

The literature review provided a basis to develop a conceptual model of ABM (see chapter 4) that particularly described the probable agents, causality in the process and probable relationships amongst the agents as well as between agents and environment. It provided a basis to generate a basic computerised model. The conceptual model is described using the ODD + D (Overview, Design Concepts and Details) protocol as explained by Müller et al. (2013). ODD description aids in creating factual model description that is quick and easy to grasp and has a consistent order (Grimm et al., 2010). Table 2 exhibits the elements of an ODD protocol originally proposed by Grimm et al., (2010). The overview segment helps in identifying the basic elements of the model such as entities, state variables (properties of the agents) and scales (spatial and temporal) of the model along with the basic description of processes in the model. Design concepts describe the basic concepts that the model is implementing which are important for designing the ABM. For example, the concept of emergence that focuses on what results and outputs can the model provide and what are the probable reasons for behind them. Details section aids in finalising the initial settings, input data and the sub-models (small processes) in the model (Railsback & Grimm, 2012).

Table 2 ODD protocol

	Elements of the ODD Protocol
Overview	1. Purpose 2. Entities, state variables and scales 3. Process overview and scheduling
Design Concepts	4. Design Concepts • Basic Principles • Emergence • Adaptation • Objectives • Learning • Prediction • Sensing • Interaction • Stochasticity • Collectives • Observation
Details	5. Initialization 6. Input data 7. Sub-models

Source: Grimm et al. (2010)

3.2.3. Development of Computerized ABM

After finalising the conceptual model, the model was then translated to a computerised environment using the software NetLogo (Wilensky, 1999). NetLogo aided in carrying out several simulations that helped understand the causality and overall impact of microfinance on the disaster risk. The model was developed step-wise with the addition of each process as described in chapter 4. However, due to time limitations, the model could only be developed with limited complexity.

3.2.4. Understanding the Emerging Pattern

As explained in the introduction, the model was generated to understand the role of microcredit and its intervention in case of disasters in an informal settlement. With the help of a literature review and an understanding of the topic, the model inputs as mentioned in Table 3 and the values that should be varied were decided. The outputs are presented in Table 4 along with their rationale for investigation and their favourable values based on the literature. The results of the study were compared to the favourable values to understand whether the model is providing the results that are conforming with the literature review. Moreover, scenarios such as; microcredit service without disaster, microcredit service with disaster but without relief funds, and microcredit with disasters and relief fund were presented in the results section.

Table 3 Model inputs and their values

S. No.	Model Parameters	Values
1	Initial funds with MFI	5000, 10000, 20000, 50000 ($)
2	Relief-funds-given?	true false
3	Disaster?	true false
4	loaned-amount	50 100 150
5	residents-wanting-loan initially	30 60 90 120 150
6	Repayment-period	8 10 12 14 16
7	Preference-low-productivity?	true false
8	Influence-residents	1 2 3 4 5
9	Interest-rate	20 40 60 80
10	Frequency-disaster	12 24 36 48 60

Table 4 Outputs from the model and their rationale for investigation

S. No	Important outputs from the model	Favourable values	Rationale for investigation
1	Total number of residents with owned business	Should be more	The main motive of MFIs is to provide credits to build a livelihood (small business) of a resident. Therefore, it is important to study the circumstances in which this output can be maximized.
2	Total number of defaulters	Should be less	Although MFIs intend to be helpful, to maintain the available funds to make the credits available always, they must increase the cost of a loan. In many cases increase in costs of loan puts pressure on the residents increasing in a number of defaulters. To avoid this, this output needs to be studied.
3	Time taken for the simulations to stop	Should be shorter	MFIs are helpful only if the results are seen in the time frame of a few years. If it is taking a long time, not many residents might opt for these services. Therefore, it is important to understand the factors that are allowing most of the residents to own the business as well as end the simulation faster.
4	Average productivity of residents in the end	Should be higher	The average productivity of the residents in a settlement is a measure of how well the residents are. Therefore, the simulations where average productivity

S. No	Important outputs from the model	Favourable values	Rationale for investigation
			has increased by the end of the simulation need to be examined.
5	Average time taken by the residents to get the loan	Should be shorter	Accessibility to the credits from MFIs is the first step towards owning the business. Therefore, it is important to understand the conditions that lead to a shorter average time to obtain the loan.
6	Average time taken by the residents to own the business	Should be shorter	Along with the number of residents with an owned business, it is important to understand whether the business is owned in a rational amount of period. The shorter value of this output will suggest that most of the residents have owned the business in a shorter time.
7	Funds with MFI at the end of a simulation	Should be higher	As MFIs also work for generating some profit along with the provision of credits, it is important to identify conditions where MFIs have larger amount of money by the end of the simulation.

3.2.5. Sensitivity Analysis

Sensitivity analysis is described as the way in which the output of the model is changed with respect to different values of model input (Saltelli, Tarantola, Campolongo, & Ratto, 2004). Sensitivity analysis helps to evaluate the model results comprehensively and quantitatively. It can aid in analysing both a model and the system represented by a model (Grimm & Railsback, 2005). Moreover, according to Sargent (2010) sensitivity analysis is also considered to aid in validating the model.

Furthermore, there are two types of sensitivity analyses that can be done in this context; local and global (ten Broeke, van Voorn, & Ligtenberg, 2016). Local sensitivity analysis often termed as OAT (One-at-a-time), consists of varying one parameter at a time while fixing all other parameters to a certain value. This way it aids in revealing the form of relationship between the varied parameter and the output considering all other parameters having a fixed value (Cariboni, Gatelli, Liska, & Saltelli, 2007). The global sensitivity analysis as explained by Saltelli et al. (2004) considers the variation in all the parameters for testing the output. This type of analysis is usually done using a regression model analysis (ten Broeke et al., 2016). As there are several model inputs (parameters), it is necessary to study a variation in all the parameters at the same time. Therefore, regression analysis is chosen to perform global sensitivity analysis in this study. Grimm and Railsback (2005) also mention that regression methods can help identify and parametrize the relationships between model inputs and model outputs. Therefore, a linear regression method is used in this study. Although global sensitivity analysis also ascertains the identification of interaction effects by taking a wide range of parameter values (ten Broeke et al., 2016), due to limited time, analysis of interaction effects were not performed in this study.

A regression analysis was carried out for various outputs (see chapter 5) of the model to perform a sensitivity analysis. Model inputs as mentioned in Table 3, were chosen with the help of literature review and were varied to the extremes. With the help of regression analysis, the significance of parameters in predicting the output and the level of importance of the parameter was identified using the significance of t-value at 99% confidence interval and unstandardized coefficient Beta respectively. All the parameters were also tested for multicollinearity using tolerance and VIF values. If the tolerance is > 0.2 and VIF value is less than 10, the predictors were considered to be non-collinear (A. Field, 2009). Apart from this, the R square value along with ANOVA F-value was observed for each regression analysis to ensure that the regression model was effectively explaining the variance in the data and it is a significant fit for the data.

To have a comprehensive view, the results from regression were summarized in a table form, and then the most favourable value for all the parameters was decided to ensure a better output (see favourable values in Table 4). This process was done for two scenarios; one scenario was without the disasters which helped in understanding the functioning of MFI in general. The other scenario was with the disaster including the intervention of MFIs in case of disasters. Furthermore, the favourable values of inputs and outputs obtained from sensitivity analysis were further investigated for better understanding.

3.2.6. Formulating Results

Simulations with the inputs mentioned in Table 3 were run using Behavior Space tool in NetLogo. As there were many simulations, owing to the limited time, simulations were only studied for a single time-step i.e. after 10 years (120 months). A time period of 10 years was given to incorporate once in 5 years of disaster into the model. Random-seed helps in obtaining the same initial conditions for each simulation and makes the simulations comparable (Wilensky, 1999). A random-seed of 11 was used to generate simulations. After obtaining the simulations, regression analysis was done using SPSS for the outputs mentioned in Table 4. The simulations for few outputs were filtered as mentioned in Table 5 in order to avoid unusual results from the regression analysis.

Moreover, to visualise the patterns that emerged from the model, line graphs were used. The results were critically discussed to identify usefulness of relief funds initiative by MFIs and under what condition are these relief funds useful. Furthermore, the usability of the developed ABM was also discussed along with its limitations.

Table 5 Simulations considered for regression analysis

S. No	Important outputs from the model	Simulations taken into consideration	Reason
1	Total number of residents with owned business	All	-
2	Total number of defaulters	All	
3	Time taken for the simulations to stop	Only the simulations that had number of residents with owned business greater than or equal to 50%	As there were simulations with very less residents owning the business and time taken by the simulations was also shorter. Such cases would have influenced the regression result.
4	Average productivity of residents in the end	All	-

S. No	Important outputs from the model	Simulations taken into consideration	Reason
5	Average time taken by the residents to get the loan	Only the simulations that had number of residents that have received the loan greater than or equal to 50%	Simulations with residents that have a smaller number of residents receiving the loan might have a very larger value of this output. To avoid the influence of such cases in the regression analysis, selected simulations were taken.
6	Average time taken by the residents to own the business	Only the simulations that had number of residents with owned business greater than or equal to 50%	Simulations with residents that have a smaller number of residents owning the business might have a very larger value of this output. To avoid the influence of such cases in the regression analysis, selected simulations were taken.
7	Funds with MFI at the end of a simulation	All	-

4. CONCEPTUAL FRAMEWORK OF MODEL

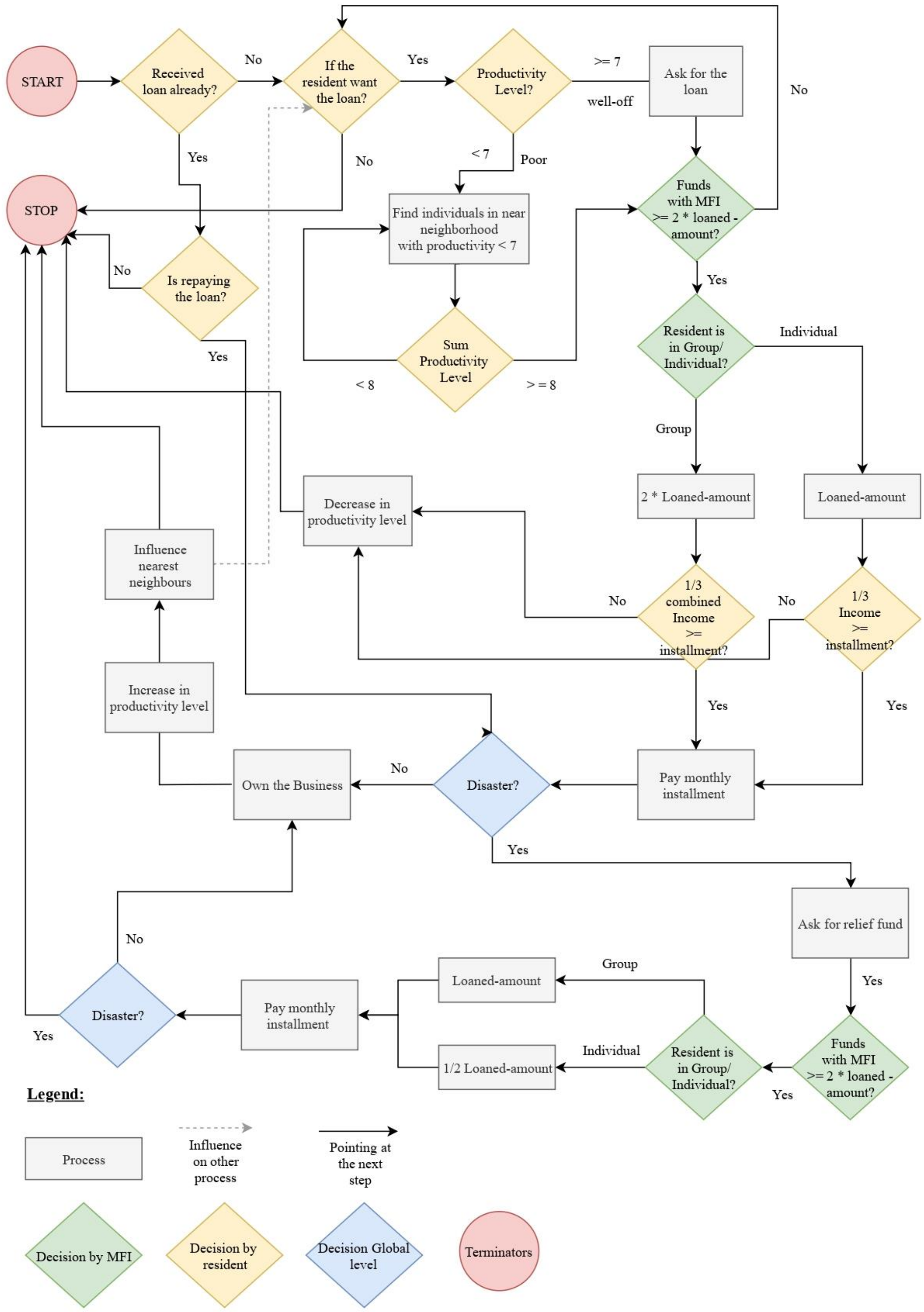


Figure 2 Flowchart of processes in the model that could happen within a tick

With the help of literature review, all the elements of the model have been constructed and described in the form of ODD+D (Overview, Design Concepts and Details) as explained by Müller et al. (2013). The processes in the model are presented in Figure 2.

Following sections describe the model in the format of ODD + D.

4.1. Overview

4.1.1. Purpose of the Model

4.1.1.1. What is the purpose of the model?

The model aims to investigate the role of microcredit service along with the intervention of relief fund and rescheduling of repayment period in case of disaster an informal settlement using ABM.

4.1.1.2. For whom is the model designed?

The model is designed for the researchers who wish to study microcredit in case of disasters and for the policymakers who are keen to utilise microcredit in case of disaster.

4.1.2. Entities, State Variables and Scales

4.1.2.1. What kinds of entities are in the model?

The model has two types of entities: residents and an MFI. There are one MFI and 300 residents in the model.

4.1.2.2. By what attributes (i.e., state variables and parameters) are these entities characterised?

The residents are characterized by their productivity level, their want for a loan, their monthly income after setting up a business[2], the status of a loan (asked for a loan already?). Table 6 describes the state variables of residents and their values in the model.

Table 6 State variables of residents and their description

S. No.	State Variables	Description	Values in the model
1	Productivity Level	Productivity level refers to the credit history and collaterals that a resident has.	1 to 11
2	Monthly Income	This is the income that each resident earns after setting up the business. It is proportional to the productivity level.	40 to 60 units[3]

MFIs are characterized with the funds they have. These funds can be varied in the initial stage of with the help of a slider to see the effects. Table 7 describes the state variable of MFI.

Variables such as interest rate, repayment period, amount of loan (credits), preference by MFI for providing loans either to the poor or the rich, frequency of disasters, whether MFI provides relief funds or not, number of residents that are influenced by each successful resident and residents wanting the loan initially, affect the residents as well as the MFI. Therefore, these are part of the global environment. These variables also will

[2] The income of residents is important to decide whether they will be able to repay the credit in instalments.
[3] As the values discussed in the literature review are in $ (dollars), the units are also in dollars.

be varied with the help of a slider or a switch (Refer Annexure- I, Figure 34). Table 9 describes the global variables in the model.

Table 7 State variables of MFI and their description

S. No.	State Variables	Description	Values in the model
1	Funds with MFI	The money that is available with MFI	Any amount above zero

4.1.2.3. What are the exogenous factors/drivers of the model?

Disasters are the exogenous factors/drivers of the model.

4.1.2.4. If applicable, how is space included in the model?

Each patch represents the place of residence of the resident on that patch. As the model is stylized, the size of the patch does not affect the model outputs. It is assumed that MFI is located in the centre of the settlement.

4.1.2.5. What are the temporal and spatial resolutions and extents of the model?

Each tick in the model represents one month. The temporal extent of the model is decided by either of the three conditions below in sequence. If the first condition is false, then the model will check for the second condition, and if both the initial conditions are false, the model will stop running after 120 ticks.

1. Till the time all the residents with loan have either paid back or become defaulters[4] , and MFI is out of funds.
2. Till the time all the residents own a business or become a defaulter
3. Until 120 months (10 years)

The spatial resolution is not relevant in this context.

4.1.3. Process Overview and Scheduling

4.1.3.1. What entity does what, and in what order?

In each time step, residents without a loan and with a want for loan **ask for a loan** from MFI to start a small business. MFIs, based on the productivity level of residents/groups (higher/lower productivity resident/group will be preferred based on selected preference by the observer) and available funds, **sanction the loans**. Individual or a group set up the business and starts selling the product/service and repays the first instalment within the same month.

Within one month, an individual or group **starts repaying the loan**. With this repayment, MFIs get their money back in instalments and increase their available funds. Once the loan is repaid in mentioned repayment period, individuals/groups **own the business** and increase their productivity level. Moreover, the resident with an owned business **influences** his/her neighbours for asking the loan depending upon the value selected in the slider of influence. In this process, if a disaster has occurred, individuals/groups who are in the process of repaying the loan will **get half of the loan amount as an emergency loan.** Apart from the emergency loans, MFIs will **reschedule** the repayment period of individuals/groups who are in

[4] Defaulters term is used for the residents that are unable to repay the loan

the process of repaying the loan, by increasing their time limit by half of the repayment period provided initially. The system will stop if one of the three conditions mentioned above is true.

4.2. Design concepts

4.2.1. Theoretical and Empirical Background

4.2.1.1. Which general concepts, theories or hypotheses are underlying the model's design at the system level or at the level(s) of the sub model(s) (apart from the decision model)? What is the link to the complexity and the purpose of the model?

The model is based on the provision of microcredit by MFI to residents at certain interest rate and repayment period. Based on the literature review, the calculation of the amount of instalment is done based on flat-rate method.

Another concept used in the model is related to the group and individual loan. The model specifically incorporates that the poor will have to formulate groups to apply for loans whereas only the well-off can get the individual loan.

Social networks are also incorporated in the model. It is assumed that each successful resident can influence some of his neighbours to opt for these loans.

4.2.1.2. On what assumptions is/are the agents' decision model(s) based?

Assumption 1: Any individual or group can ask for the loan only once. Therefore, if a resident becomes a defaulter i.e. is unable to repay the loan cannot ask for a loan again.

Assumption 2: The individual or group member earn the same amount of money every month. The resident repays the loan only if one-third of the income is greater than or equal to the monthly instalment.

Assumption 3: If the resident has owned the business, he/she will now no more depend on the MFI for credit services. Therefore, if the resident is in the process of repaying the loan, he/she will ask for a relief fund. If the resident has owned the business or became a defaulter, the resident won't ask for a relief fund.

Assumption 4: Disaster always has a similar intensity; therefore, a similar amount of relief is provided to the residents. Therefore, residents ask for the same amount of relief fund for any frequency of disaster.

Assumption 5: It is assumed that MFIs have a certain preference while selecting a client. MFIs provide loan and relief fund to either the highest productivity level resident or the lowest depending upon the slider.

4.2.1.3. Why is/are certain decision model(s) chosen?

The decision model is chosen to explain the process of microcredit service and disaster in the simplest possible way.

4.2.1.4. If the model/sub-model (e.g. the decision model) is based on empirical data, Where do the data come from?

The model is not based on empirical data.

4.2.1.5. At which level of aggregation were the data available?

Not Applicable.

4.2.2. Individual Decision-Making

4.2.2.1. What are the subjects and objects of decision-making? On which level of aggregation is decision-making modelled? Are multiple levels of decision making included?

The subject of decision making is residents and MFI. The decision making is observed at two levels, MFI level and household level.

The objects of decision making for residents are; Asking for loans, Repayment of loan, Formulating group.

The objects of decision making for MFI are; Provision of loan or relief fund, Provision of the amount of loan and relief fund

4.2.2.2. What is the basic rationality behind agent decision-making in the model?

The residents ask for a loan because they want it. They repay the loans as it is needed to own the business. The residents formulate a group to become eligible for obtaining the loan.

The MFIs provide the loan and relief funds to benefit the residents and also to gain profits.

4.2.2.3. Do agents pursue an explicit objective or have other success criteria?

Objective of MFI – To provide loans in general and relief funds during a disaster.

Objective of resident – To ask for loans provided by MFIs if they want.

4.2.2.4. How do agents make their decisions?

Decisions by Residents:

Asking for loans

The residents ask for loan – If productivity level ≥ 7 – then they ask for loan directly,

If productivity level < 7 – They formulate group and ask for the loan

Repayment of loan

The residents that are in a group can repay the loan if their 1/3 Combined Income ≥ instalment

The residents that are not in a group (individual) can repay the loan if their 1/3 Income ≥ instalment

Formulating group

If the productivity of the resident is less than 7 and is wanting the loan then the resident approaches the nearest neighbour resident that has productivity less than 7 and wants the loan. If the sum of their productivity is equal to 8 or above, then they form a group and ask for loan. If not, then the resident that approached the nearest neighbour finds another resident near to him/her, and if the productivity of three of them is greater than or equal to 8, then the group is formed. This goes on until the sum of the productivity is 8 or above.

Decisions by MFI:

The MFI provides relief funds first if there is a disaster in that step and then the loans are provided to the residents that are waiting for loans.

The MFI provides double the selected loaned-amount to groups and loaned-amount to individuals asking for a loan. The MFI provides loaned-amount to groups and half of the loaned-amount to individuals asking for a relief fund.

4.2.2.5. Do the agents adapt their behaviour to changing endogenous and exogenous state variables? And if yes, how?

Residents, if in the process of repaying the loan, stop and ask for relief funds from MFI in case of disaster.

Depending upon the frequency of disaster and residents that are wanting relief funds, MFI provides the relief funds.

If the MFI has a financial approach, they prefer the highest productivity resident to provide loans and relief funds. If the MFI has a poverty approach, then they prefer the lowest productivity resident to provide loans.

Based on the number of residents getting influenced by each successful resident slider, each resident influence that many numbers of residents only if that many numbers of residents are there. If there are a number of residents lesser than the value in the number of residents getting influenced by each successful resident slider, then the resident does not influence any resident.

4.2.2.6. Do social norms or cultural values play a role in the decision-making process?

The successful residents are assumed to influence other residents in the neighbourhood. This is one of the social norms that is used in the decision-making process of influencing.

4.2.2.7. Do spatial aspects play a role in the decision process?

No.

4.2.2.8. Do temporal aspects play a role in the decision process?

No.

4.2.2.9. To which extent and how is uncertainty included in the agents' decision rules?

Uncertainty is not included in agents' decision rules.

4.2.3. Learning

4.2.3.1. Is individual learning included in the decision process? How do individuals change their decision rules over time as a consequence of their experience?

The individuals stop formulating group once the sum of their productivity is 8 or above. Apart from this, there is no individual learning in the decision process.

4.2.3.2. Is collective learning implemented in the model?

No.

4.2.4. Individual Sensing

4.2.4.1. What endogenous and exogenous state variables are individuals assumed to sense and consider in their decisions? Is the sensing process erroneous?

Individuals sense the disaster

4.2.4.2. What state variables of which other individuals can an individual perceive? Is the sensing process erroneous?

Individuals can sense the location of other residents and formulate groups based on the nearest resident. The residents in the group sense each other's income as their repayment ability depends upon their combined income. Also, while formulating the group residents sense each other's productivity after interacting with each other. However, there is interaction based on their income or productivity level directly.

4.2.4.3. What is the spatial scale of sensing?

The nearest neighbour can be any resident from the entire space which is located at the nearest distance.

4.2.4.4. Are the mechanisms by which agents obtain information modelled explicitly, or are individuals simply assumed to know these variables?

Individuals are assumed to know the variables.

4.2.4.5. Are the costs for cognition and the costs for gathering information explicitly included in the model?

No

4.2.5. Individual Prediction

4.2.5.1. Which data do the agents use to predict future conditions?

Agents are not predicting any future condition

4.2.5.2. What internal models are agents assumed to use to estimate future conditions or consequences of their decisions?

Not Applicable

4.2.5.3. Might agents be erroneous in the prediction process, and how is it implemented?

Not applicable

4.2.6. Interaction

4.2.6.1. Are interactions among agents and entities assumed as direct or indirect?

The interaction between residents and MFI and between the agents is direct.

4.2.6.2. On what do the interactions depend?

The residents interact with MFI to ask for a loan. After the interaction, if MFI has enough funds, the resident gets the loan and MFI lose that many funds. Also, residents and MFI interact when residents have to repay the loan and when residents want relief funds.

The residents interact with each other to formulate groups.

4.2.6.3. If the interactions involve communication, how are such communications represented?

The communication is represented in terms of gain and loss of funds when the interaction is between MFI and residents.

The interaction between residents is represented with a link between them, and the group productivity value is changed for both the residents.

4.2.6.4. If a coordination network exists, how does it affect the agent behaviour? Is the structure of the network imposed or emergent?

Not applicable

4.2.7. Collectives

4.2.7.1. Do the individuals form or belong to aggregations that affect and are affected by the individuals? Are these aggregations imposed by the modeller or do they emerge during the simulation?

As mentioned above, individuals aggregate to formulate groups to apply for loans. The modeller imposes the aggregations.

4.2.7.2. How are collectives represented?

The collectives are represented as a group of residents.

4.2.8. Heterogeneity

4.2.8.1. Are the agents heterogeneous? If yes, which state variables and/or processes differ between the agents?

The agents are heterogeneous based on their productivity level and income. However, income is directly proportional to the productivity level.

4.2.8.2. Are the agents heterogeneous in their decision-making? If yes, which decision models or decision objects differ between the agents?

The agents are not heterogeneous in their decision making.

4.2.9. Stochasticity

4.2.9.1. What processes (including initialisation) are modelled by assuming they are random or partly random?

The productivity of residents, the initial location of the residents and the order in which they ask for a loan and formulate group, is randomised at every setup.

4.2.10. Observation

4.2.10.1. What data are collected from the ABM for testing, understanding and analysing it, and how and when are they collected?

The data that are collected from the model are mentioned in Table 8.

Table 8 Data collected from the ABM

S. N	Data collected from the model
1	Total number of residents with owned business
2	Total number of defaulters
3	Time taken for the simulations to stop
4	Average productivity of residents in the end
5	Average time taken by the residents to get the loan
6	Average time taken by the residents to own the business
7	Funds with MFI at the end of a simulation

.

Other datasets like number of residents receiving a loan from MFI and number of residents wanting the loan are also collected for testing; however, a sensitivity analysis is not carried out for them.

Apart from this, the outputs of number of number of residents with owned business and average productivity by the end of the simulation suggest that if they are larger, the adaptive capacity of the residents is increased.

All the outputs are collected for every step until the process stops.

4.2.10.2. What key results, outputs or characteristics of the model are emerging from the individuals? (Emergence)

The average productivity of the residents is changing. A number of residents are either owning a business or becoming defaulters.

4.3. Details

4.3.1. Implementation Details

4.3.1.1. How has the model been implemented?

The model is implemented using NetLogo software.

4.3.1.2. Is the model accessible, and if so where?

The code for this model is added in the appendix.

4.3.2. Initialisation

4.3.2.1. What is the initial state of the model world, i.e. at time t = 0 of a simulation run?

There are total of 300 residents in total. None of the residents has received any loan or owned any business. Few residents based on the global variable of number of residents wanting a loan initially want the loan. Every resident is assigned to a productivity level. All the residents have their income as zero $. None of the residents is affected by the disaster.

Based on the productivity level these residents will apply for individual or group loan. The productivity level is randomly assigned to all the residents from 1 – 10. The number of residents wanting the loan will be decided using the slider. Moreover, an equal number of residents with productivity less than 7 and greater than or equal to 7 is assumed to want the loan in the beginning. Initially, all the agents will not be affected by the disaster. The income will be set as 0$ initially for all.

4.3.2.2. Is the initialisation always the same, or is it allowed to vary among simulations?

The initialisation can vary based on the values of global variables on the sliders of the model. Moreover, the distribution of productivity level is random; therefore, changes at every step. Moreover, a random set of residents has a want for loan at every setup.

4.3.2.3. Are the initial values chosen arbitrarily or based on data?

For productivity initial values are given as 1 to 10 randomly. However, as residents above the productivity level of 7 are rich, there is a smaller number of well-off residents as compared to poor. This has been assumed as the number of the poor is larger than a number of well-off in informal settlements.

4.3.3. Input Data

4.3.3.1. Does the model use input from external sources such as data files or other models to represent processes that change over time?

No.

4.3.4. Sub-models

4.3.4.1. What, in detail, are the sub-models that represent the processes listed in 'Process overview and scheduling'?

A detailed process of the model is shown in figure 2.

1. Ask a loan:

If the productivity level of residents is greater than or equal to 7, the residents can ask for individual loans. If the productivity level of residents is less than 7, the residents formulate group for loans.

MFIs will provide loans to the resident with highest/lowest productivity (depending on the model parameter) if the funds are available. If not, the system will stop.

2. Formulate a group:

The sum of the productivity level of residents in a group should be more than or equal to 8 (This process will ensure that a more productive group that is sensitive to repayment is generated). Each resident will find a group-mate in his neighbourhood (nearest distance-wise) and stop if the productivity level is >= 8. In each time-step, the resident will find one group-mate and evaluate its productivity level. If it is >= 8 then, stop. If not, the resident will find one-more group-mate in the same time-step.

3. Repay the loan:

Once the business is owned, the income of individuals and groups will be 40-60$ per month. It will be assigned in a way that individual with higher productivity generates higher income. For group borrowers also, it will be the same.

The calculation of the amount to be repaid (loaned amount + interest) will be done using the flat-rate method as it is the most common method used by MFIs (Explained in chapter 2). The formula is:

Amount to be repaid = loaned amount + loaned amount * (interest-rate / 100)

Instalment = Amount to be repaid / Repayment period

If the instalment is more than one-third of the income, the resident won't be able to pay the loan and will be a defaulter.

Around one-third of the income can be paid as the instalment by individual and group (assuming another two-thirds is the expenditure)

In the case of a group, if instalment is more than one-third of the total income of group members, then they won't be able to pay the loan and will be a defaulter.

After setting up the business, the group/individual pay their first instalment to the MFIs. This way, their loaned amount reduces to (original amount – instalment). This also adds up to available funds of MFIs. This happens in every time-step (Along with asking for loans if there is some loaned amount on residents).

4. Obtaining relief funds

The residents already registered with MFIs and have not paid the loan completely, will get emergency funds depending upon the occurrence of a disaster (half of original loaned). They will also get an extended repayment period (extra half of the original repayment period).

5. Own the Business

Once the entire loaned amount with interest is repaid, the individual/group owns the business and becomes economically stable. (Increases productivity level). If a resident has become a defaulter, the productivity level of resident decreases.

6. Influence

Once the resident has owned the business, resident influences other residents that are located near to him/her. The number of residents that are getting influenced by each resident is decided by the value of the model parameter.

4.3.4.2. What are the model parameters, their dimensions and reference values?

Table 9 presents model parameters and their reference values.

Table 9 Global variables and their description

S. No.	Global variables	Description	Reference Values
1	Initial funds with MFI	Funds available with MFI during the initiation.	5000, 10000, 20000, 50000 ($)
2	Interest Rate	Rate at which the loans are given out by MFIs	20 40 60 80
3	Repayment Period	The period for which loans are given out by MFIs	8 10 12 14 16
4	Amount of Loan[5]	The amount of loan [6] taken by residents.	50 100 150
5	Preference?	If the preference is given to the poor or the well off.	true false
6	Residents Wanting Loan	Number of residents wanting the loan at the initiation	30 60 90 120 150
7	Residents getting influenced	Number of residents that are getting influenced by each successful resident	1 2 3 4 5
8	Frequency of disasters	The frequency at which disaster will occur. In the model the value is kept as once in 1, 2, 3, 4, or 5 years.	12 24 36 48 60 months
9	Relief fund provided?	If the relief fund and restructure of repayment is provided or not.	true false
10	Disaster?	If there are disasters or not	true false

4.3.4.3. How were the sub-models designed or chosen, and how were they parameterised and then tested?

The sub-models were designed step-by-step and tested in NetLogo itself.

[5] The model input of amount of loan does not relate to the development of a better business. It only is discussed in the context of resident's ability to repay.
[6] Amount of loan for groups is twice the amount of loan offered to individuals

5. MODEL RESULTS

This chapter presents the outputs of the model that is generated using NetLogo. The outputs are presented with respect to three research questions of the third objective. The model is generated to investigate microcredit and the intervention of relief fund in the context of disaster in an informal settlement. The chapter first presents the overview of microcredit service without any disaster. Thereafter, it explains the effect of disaster on microcredit service followed by the intervention of relief funds in the context of disaster. Lastly, the results of sensitivity analysis are presented.

5.1. Overview of Emerging Pattern from the Model

As the model assumes that residents only use microcredits to uplift their statuses, the model cannot explain the scenario without the microcredit service. However, the model can explain the scenarios with microcredit without any disaster, with microcredits and disaster without relief funds, with microcredits and relief funds in case of disaster. Therefore, the following sections describe the scenarios given in Table 10. In order to compare the two scenarios a few input variables such as residents wanting the loan initially, a number of residents getting influenced, initial funds with MFI, loaned amount and preference were having same values. The factors of interest rate and repayment period were varied as mentioned in Table 10. The extreme values of both of these factors were chosen to elaborate upon the tentative best and the worst case. As factors of interest rate and repayment period are very crucial according to the literature review, only these parameters were varied to understand the emerging pattern from the model.

Table 10 Input variables for both the scenarios

Model Inputs	Scenario 1	Scenario 2
Initial funds	10,000	10,000
Loaned amount	150	150
Number of residents wanting the loan initially [7]	60	60
Number of residents getting influenced	3	3
Preference?	To the poor	To the poor
Interest rate	20	80
Repayment period	12	16

5.1.1. Emerging Pattern – Microcredit Service without Disaster

The first research question of the third objective is:

"What is the pattern observed after the introduction of microcredit service in an informal settlement?"

There are two parts of this research question. This section of the chapter answers the first part which describes the outputs of scenarios (refer Table 10) with microcredit service without the disaster.

This section provides an example of the outputs in the model that aid in understanding the role of microcredit service in providing an opportunity to start a business or at a broader scale, help in reducing

[7] Total number of residents in the model are 300 as mentioned in the chapter 4.

poverty. The variations over time in various model outputs such as residents wanting a loan, residents receiving the loan, residents owning the business, residents becoming defaulters, average productivity and funds with MFI are presented below for both the scenarios.

5.1.1.1. Residents wanting a loan

Figure 3 represents the number of residents who are wanting a loan at each step over time. According to the inputs mentioned in Table 10, initially, 60 residents want the loan in both the scenarios and later these residents, influence other residents after owning the business resulting in an increase of a number of residents that are wanting a loan. In scenario 1, as per the repayment period of 12, residents that received a loan at first step are owning a business by 12th step and influencing other residents to buy these loans. Therefore, at every 12th step (month), the number of residents who want the loan is increasing. Similarly, as per the repayment period of 16, in scenario 2, at every 16th step, the number of residents who want the loan is increasing. As three residents are getting influenced by each successful resident, a large number of residents are getting influenced initially, i.e. in the steps of 12 and 16 for scenario 1 and 2 resulting in a sudden increase in a number of residents wanting the loan.

Also, at the 12th and 16th step of scenario 1 and 2 respectively, not all the residents who want the loan are getting a loan (see Figure 4), therefore for a few steps ahead of 12th and 16th step for scenario 1 and 2 respectively, the number of residents wanting a loan are greater than 0.

Figure 3 Number of residents wanting the loan over time for scenarios 1 and 2

5.1.1.2. Residents receiving a loan

Figure 4 represents the number of residents receiving the loan over time. As explained in chapter 4, residents rely only on microcredits; by the end of the simulation, every resident might have wanted a loan. Therefore, as shown in Figure 4, almost all the residents receive a loan by the end of the simulation in both the scenarios. In scenario 1, residents are receiving the loan earlier as compared to scenario 2. This is because of the shorter repayment period in the case of scenario 1. Apart from this, at the 12th and 24th step of scenario 1 and the 16th and 32nd step of scenario 2, there is a sudden increase in the number of residents receiving the loan. This result corresponds with the number of residents who are wanting the loan at those steps (see Figure 3). For scenario 1, in between the steps 12 and 19, there is a gradual increase in the number of residents receiving the loan whereas, for scenario 2, it is seen in between step 16 and step 22. This suggests that few residents are required to wait for a few months to obtain the loan. Residents receive a loan only when the MFIs have the funds more than or equal to twice the amount of loan, as explained in chapter 4. The gradual increase in the number of residents receiving the loan is because of the lack of enough funds with MFIs at that time.

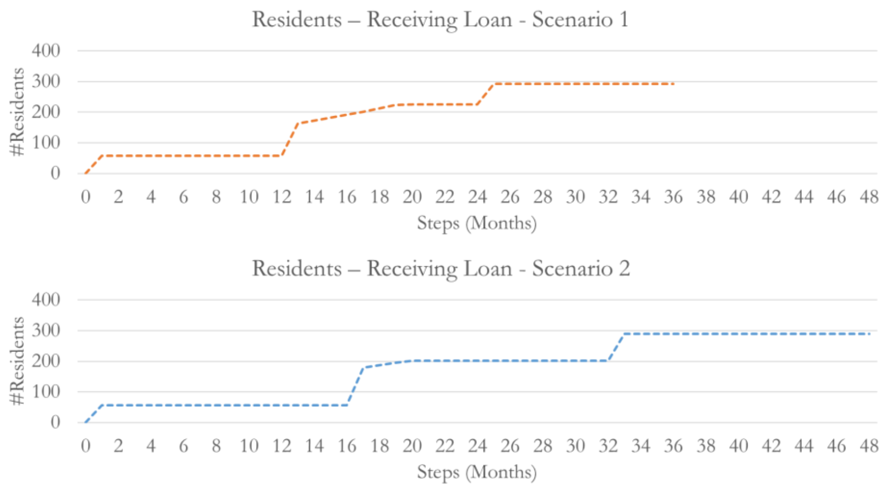


Figure 4 Number of residents receiving the loan overtime for scenarios 1 and 2

<u>Beneficiaries of the microcredits – Poor or Well-off?</u>

In both the scenarios, the residents are required to wait for obtaining the loan for a few months, as explained above. Figure 5 suggests that as preference is given to the poor, at the 12th step in scenario 1, most of the poor receive the loan whereas the well-off are receiving the loan only after the poor have received the loan. Similarly, in scenario 2 at 16th step, most of the poor are receiving the loan whereas only a few well-off residents are receiving the loan. When the preference is given to the poor, they receive the loan in a shorter time.

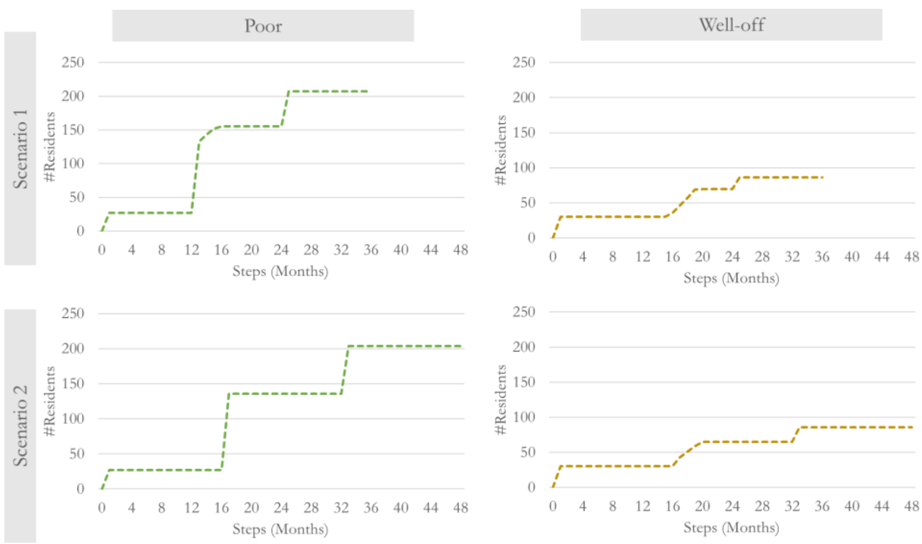


Figure 5 Number of residents receiving the loan with respect to their status overtime for the scenarios 1 and 2

5.1.1.3. Residents owning the business

Figure 6 represents the number of residents owning the business over time. As explained in chapter 4, residents own business once they have repaid the loan completely. It is evident that scenario 1 has a larger number of residents that have owned business as compared to scenario 2. This can be related to the reduction of poverty in a way that scenario 1 has helped all the residents in battling the poverty by owning a business, whereas, in scenario 2, around 60 residents have added to the poverty due to the debt. As explained in chapter 4, the resident can repay the loan if the amount of instalment is less than or equal to one-third of the income for individuals and one-third of the combined income for groups. The residents for the first scenario can repay the loan due to lower interest rate, whereas, due to the higher interest rate in scenario 2, few residents are unable to repay the loan. For scenario 1, as the repayment period is 12, in every 12th step there is a sudden increase in the number of residents owning a business. Similarly, for scenario 2, every 16th step there is a sudden increase in the number of residents owning a business.

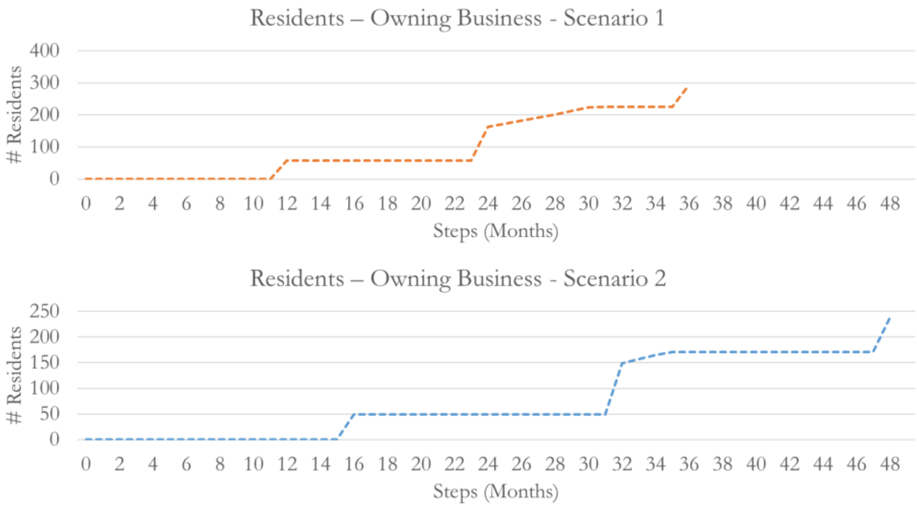


Figure 6 Number of residents owning the business over time for scenarios 1 and 2

5.1.1.4. Defaulters

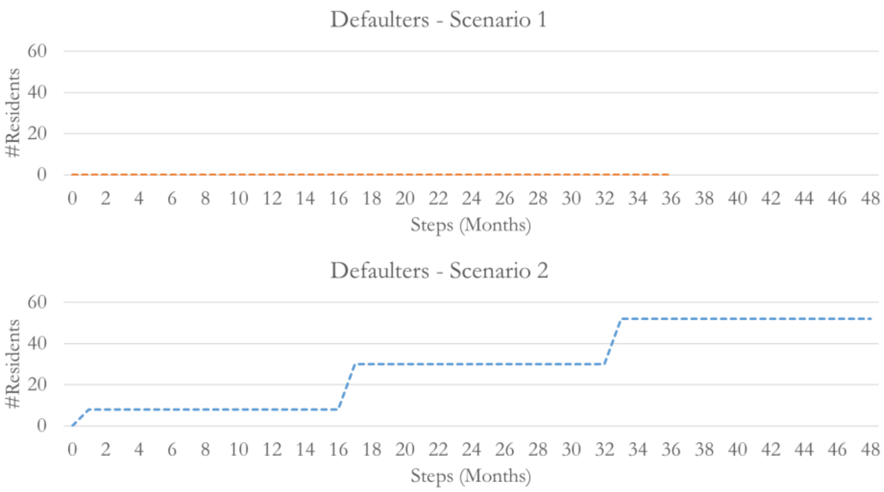


Figure 7 Number of defaulters for scenarios 1 and 2

Figure 7 represents the number of defaulters over time for scenarios 1 and 2. There are around 55 defaulters in scenario 2 whereas there are no defaulters in scenario 1.

A number of defaulters are observed at the steps where the residents have received the loan as residents repay the loan in the same step. As mentioned in the previous section, defaulters are observed in scenario 2 because of the inability of those residents to pay the loan. It is interesting to note that the size of the group influences the number of defaulters. If the last step of scenario 2 is examined, the group size of these defaulters is 2.

The ability to repay of residents after repaying the loan were plotted against the group size of residents in Figure 8. If the ability to repay (1/3 combined income or income – instalment), is zero or positive, then the residents are able to pay the loan. If the ability to repay is negative, the residents are unable to repay the loan. According to Figure 8, as the group size increases, the ability to repay the loan also increases. After the formation of the group, all the residents are having an income based on their productivity level, and a combined income of all the group members is used to calculate the ability to repay the loan. As combined income will be higher for larger sizes of groups, the ability to repay also would be higher. Moreover, in group size of 2, few residents are able to repay the loan whereas others are not. The few residents that are able to pay the loan have group productivity higher than 10.

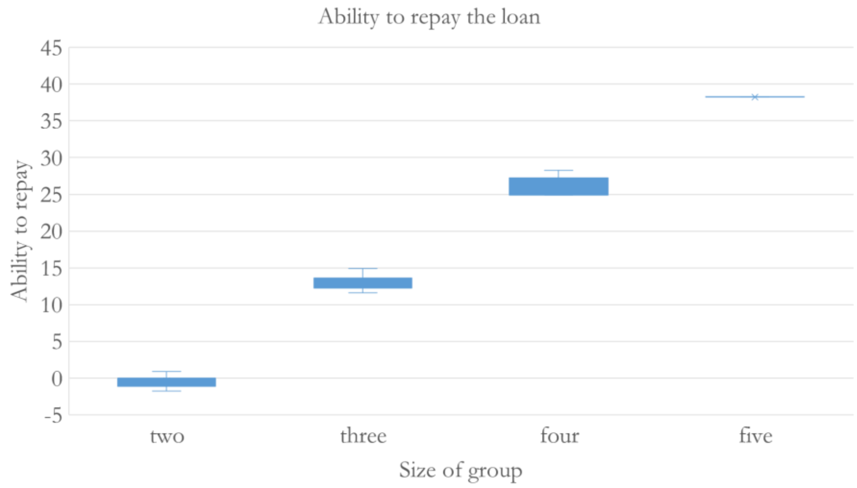


Figure 8 Ability to repay the loan vs size of the group

5.1.1.5. Average Productivity

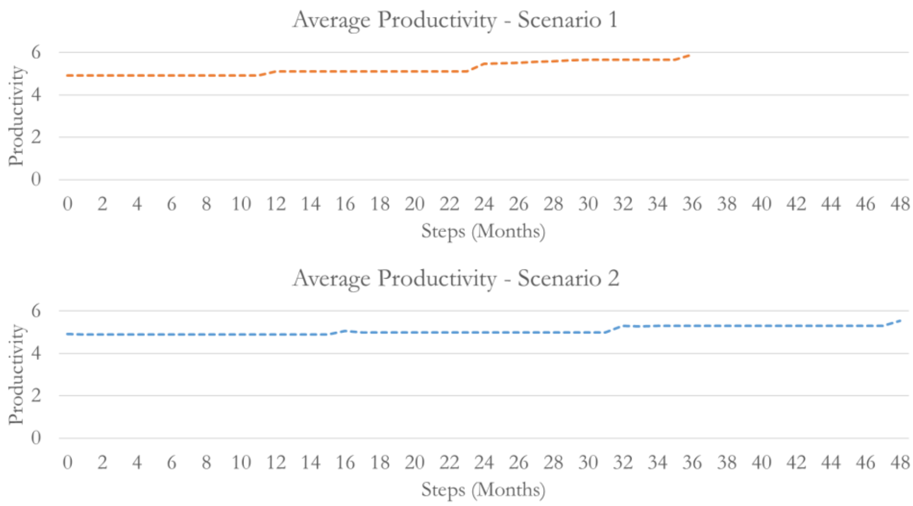


Figure 9 Average productivity over time for scenarios 1 and 2

According to Figure 9, average productivity in both the scenarios at the end of simulation is more than the initial value. As mentioned in the output of residents owning the business, this output can also be related to the impact on poverty. As average productivity is larger than the initial value in both the scenarios, it can be said that the microcredit service has been successful in reducing poverty in both the scenarios. However, scenario 1 has higher average productivity as compared to scenario 2 as a number of defaulters are observed only in scenario 2. There is a slight decrease in average productivity in scenario 2 at steps 0, 16 and 32 where the residents are receiving the loan, and few residents are becoming defaulters as they are unable to pay the loan.

5.1.1.6. Funds with MFI

Figure 10 suggests that for scenario 1 as well as scenario 2, MFI has a larger amount of funds than it had initially. However, by the end of the simulation, the funds with MFI are higher in scenario 2 than scenario 1.

Although the number of residents who have repaid the loan and owned the business is higher in scenario 1, MFI is earning more profit in scenario 2. This is mainly because of the higher interest rate at which the MFI has provided the loan in scenario 2 as compared to scenario 1. However, it is interesting to note that, by the end of the simulation of scenario 1, i.e. at 36th step, the amount of funds with MFI is higher as compared to scenario 2.

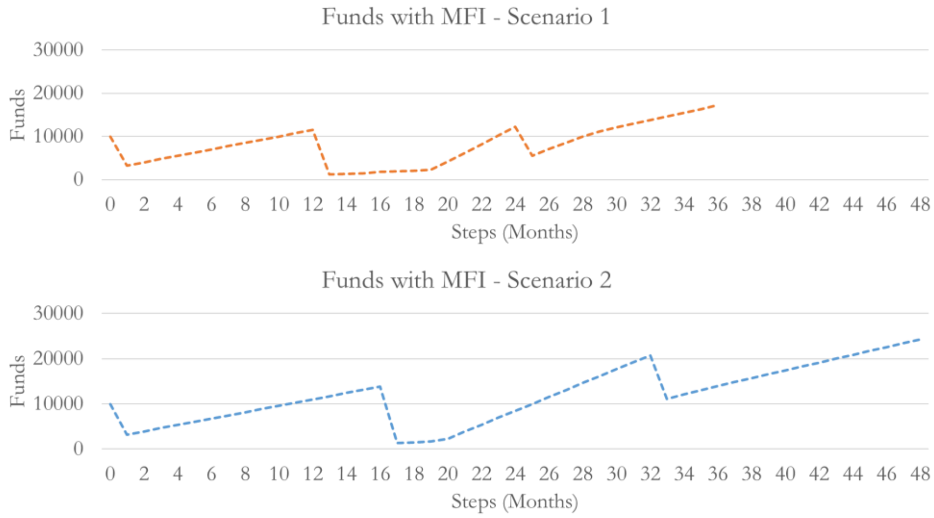


Figure 10 The funds with MFI over time for scenarios 1 and 2

5.1.2. Emerging Pattern – Microcredit Service with Disaster without Intervention

This section of the chapter answers the second part of the research question mentioned in the previous section which describes the outputs of scenarios (refer Table 10) with microcredit service and disaster. To understand the influence of disaster on the microcredit service, the highest frequency of disaster, i.e. one disaster per year is used. The outputs that are described in the above section are also described for this section. However, the descriptions also include a comparison with the situation without disaster.

5.1.2.1. Residents Wanting Loan

Figure 11 suggests that in the case of scenario 1, the pattern of residents wanting the loan with disasters is similar to the one without disasters. However, the pattern varies in case of scenario 2. It can be noticed that in the case of scenario 2, disasters interrupt the process of MFIs and the process stops at the 13th step.

5.1.2.2. Residents Receiving Loan

It is evident from Figure 12 that in the case of scenario 1, the pattern of receiving the loans by residents in case of frequent disasters is similar to the case without disasters. However, only 60 residents receive the loan in scenario 2, and the process stops after the first disaster.

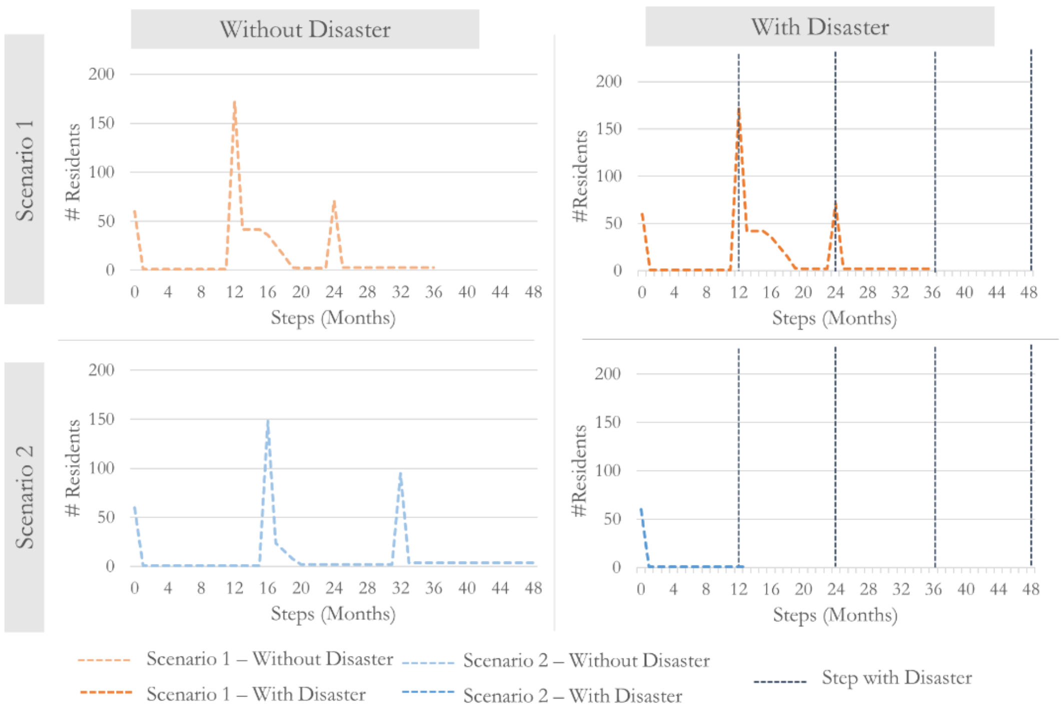


Figure 11 Residents Wanting loan over time for Scenario 1 and 2 - with disaster and microcredit without intervention

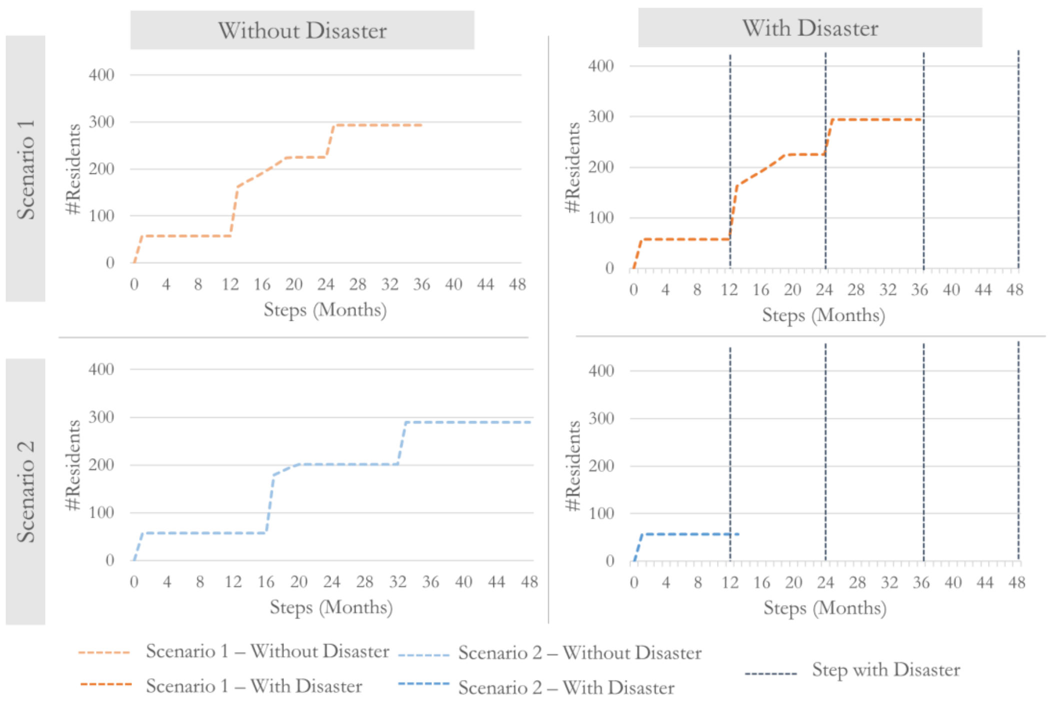


Figure 12 Residents receiving loan over time for Scenario 1 and 2 - with disaster and microcredit without intervention

5.1.2.3. Residents Owning Business

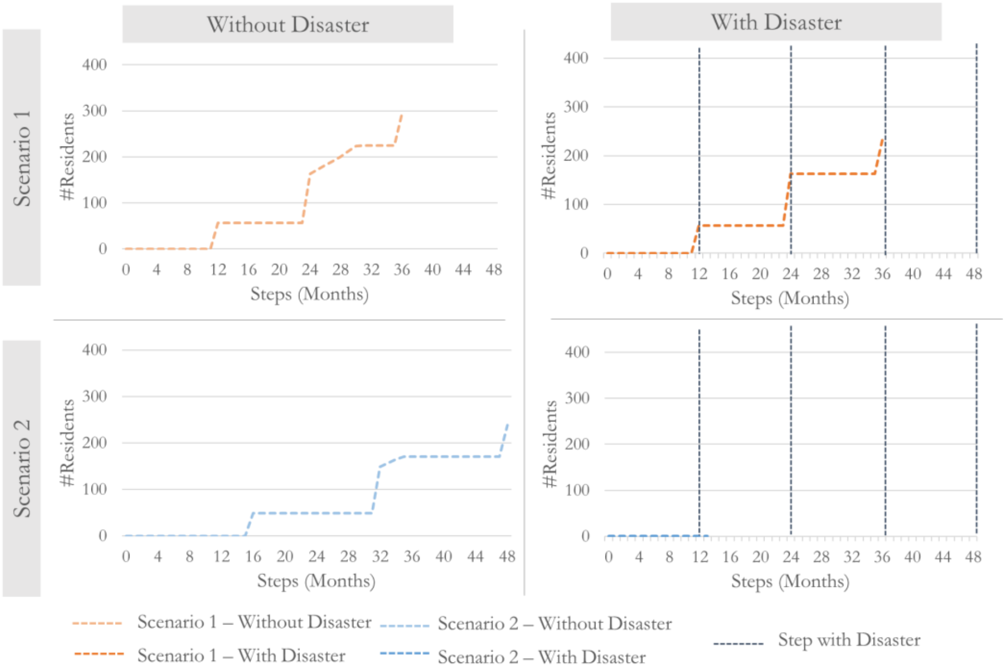


Figure 13 Residents owning the business over time for Scenario 1 and 2 - with disaster and microcredit without intervention

From Figure 13, it is evident that the disasters are affecting the pattern of residents owning the business for both the scenarios. In scenario 1, around 250 residents (83%) are owning the business in case of frequent disasters. This is because around 50 residents are receiving the loan in between 12th and 16th step (refer Figure 12) and they are unable to repay the loan before the upcoming disaster. All the residents were owning the business without the disasters. In scenario 2, none of the residents is owning the business in case of disasters. This implies that the adaptive capacity of residents is not getting improved in scenario 2 whereas it improves in scenario 1 for 83% of the residents.

5.1.2.4. Defaulters

Figure 14 suggests that around 60 defaulters are observed in scenario 1 in case of disasters while there were no defaulters without the disaster. In scenario 2, although the number of defaulters is comparable in the cases with and without the disaster, it is interesting to note that the defaulters are observed at an earlier step in the scenario with the disaster as compared to scenarios without the disaster.

5.1.2.5. Average Productivity

Figure 15 suggests that average productivity is increasing in the case of scenario 1 even with the disasters. However, by the end of the simulation, it is less than the scenario without the disasters. At the 24th step, i.e. second disaster, the average productivity is observed to be reduced, whereas, at 12th step, i.e. the first disaster, the average productivity is the same as observed in the case without disaster. In the case of scenario 2, the average productivity is less than the initial average productivity in case of disasters. This implies that the adaptive capacity of the residents has reduced here as the residents are in a debt which has increased their level of poverty.

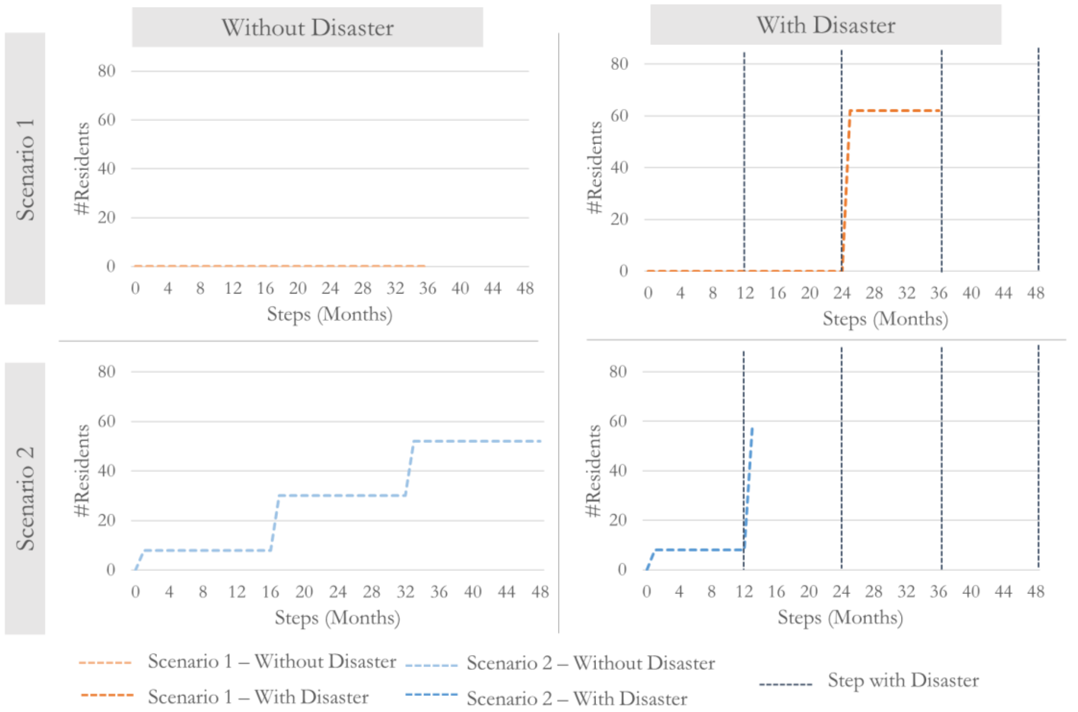


Figure 14 Defaulters over time for Scenario 1 and 2 - with disaster and microcredit without intervention

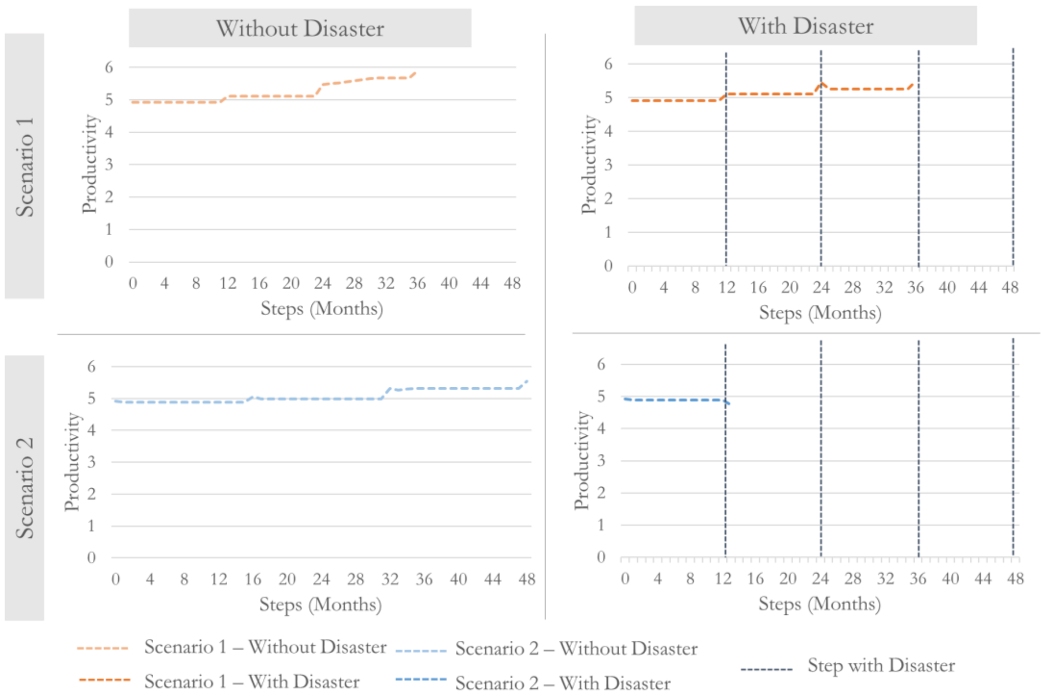


Figure 15 Average productivity over time for Scenario 1 and 2 - with disaster and microcredit without intervention

5.1.2.6. Funds with MFI

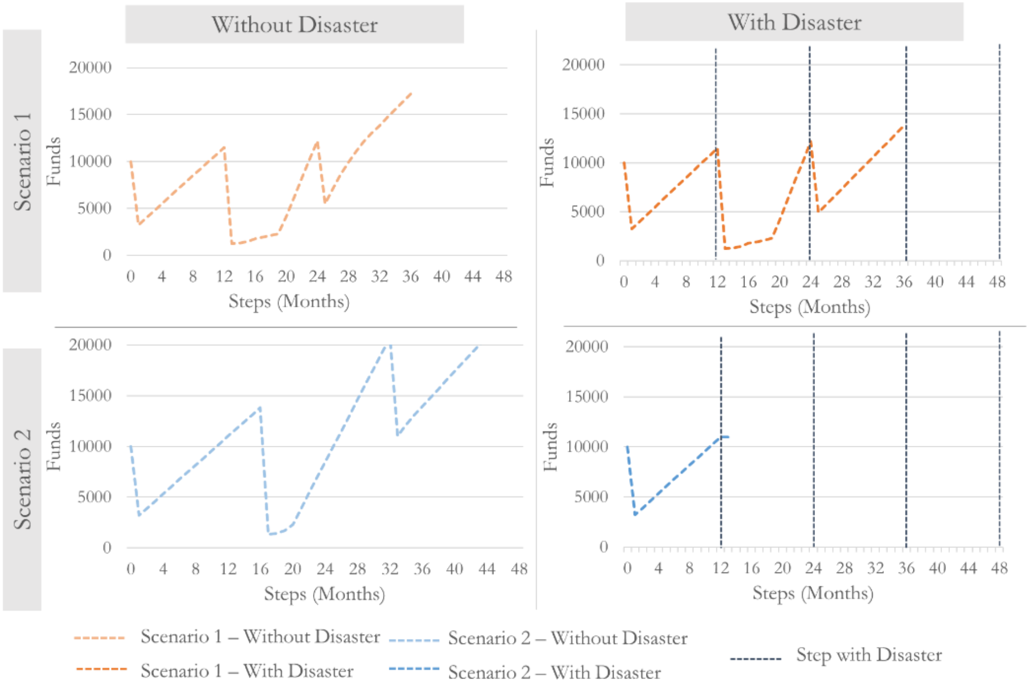


Figure 16 Funds with MFI over time for Scenario 1 and 2 - with disaster and microcredit without intervention

According to Figure 16, the funds with MFI are lesser by the end of the simulation for both the scenarios in case of disasters than without disaster. The Funds with MFI are larger than the initial amount in scenario 1 in case of disasters. In scenario 2, MFIs are able to earn little more than the initial amount they had.

It can be concluded that, although microcredits aid in reducing poverty, in case of disasters, the service might not be useful and might need some other intervention to be useful. Therefore, the following section introduces an intervention of relief funds and restructuring of loans.

5.1.3. Emerging Pattern – Microcredit Service with Disaster and Intervention

This section answers the second research question of the third objective of the study which is:

"What is the pattern observed after the intervention of MFI with respect to disaster in an informal settlement?"

It gives an overview of how the intervention of relief funds and rescheduled repayment period by MFI affects the residents for a certain frequency of disaster. Considering that the disaster is occurring per year and relief funds are provided, the changes in the two scenarios, as mentioned in Table 10, are described below. The scenarios without the relief fund stop earlier as compared to scenarios with the relief fund. This is because the intervention elongates the repayment period by half of the initial repayment period as mentioned in chapter 4. The outputs that are presented in the previous section are also presented in this case. Moreover, the outputs of residents owning a business and average productivity are related to the adaptive capacity of residents.

5.1.3.1. Residents wanting a loan – with intervention in case of a disaster

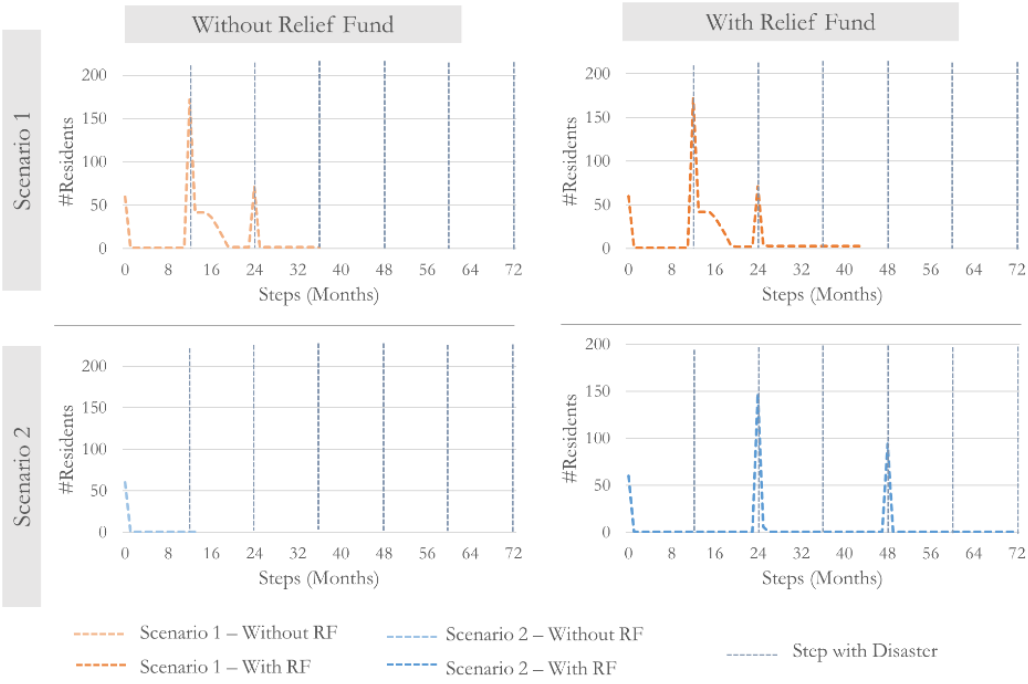


Figure 17 Number of residents wanting the loan overtime for the scenarios 1 and 2 - with intervention

Figure 17 suggests that in scenario 1, the pattern of residents wanting the loan is similar to the pattern found in the scenario without relief fund. However, the process lasts longer in case of relief funds as compared to without relief funds. For scenario 2, the number of residents wanting the loan is increasing at 24th step instead of the 16th step in section 5.1.1. Moreover, when relief funds are not provided, the process in scenario 2 stops earlier with only 60 residents receiving the loan (refer figure 17). As the relief funds are provided, the repayment period is rescheduled to 24 months. Therefore, as seen in Figure 21, the residents own the business only after 24 months, i.e. 2 years in scenario 2.

5.1.3.2. Residents receiving loans – with intervention in case of a disaster

Figure 18 suggests that initially all the residents that were wanting the loan, received the loans in both the scenarios. The pattern observed over time in receiving loans for scenario 1 is similar to the pattern observed in receiving loans without the disaster. The number of residents receiving the loan is also similar by the end of the process. However, as mentioned above, the process takes a longer time to end as compared to the scenario without relief funds. In scenario 2, the residents are receiving the loan at 24th step unlike at 16th step in section 5.1.2. It is evident that the provision of relief funds has increased the number of residents receiving the loan. Almost all the residents have received a loan in both the scenarios by the end of the simulation in the case where the relief funds are provided.

Figure 19 suggests that for scenario 1, no relief funds were provided at the occurrence of a disaster in the first year. It is interesting to note that, in scenario 1, the residents that have received the loan at 12th step (refer Figure 18) have to repay their loan by 24th step (as repayment period is 12 months) suggesting that these residents do not need any relief funds to repay their loans. However, the residents that have received the loans between 12th and 24th step will not be able to repay their loan before 24th step and therefore, require relief funds. Therefore, it is observed that the relief funds are provided only at 24th month.

For scenario 2, as the repayment period is 16 months which is longer than the frequency of disaster, the residents need relief funds to repay their loans for disasters (refer Figure 19). As after the relief funds are provided, the repayment period is rescheduled to 24 months, the residents that have received the loan initially are able to own the business at 24th step (refer Figure 21). Therefore, as shown in Figure 19, at steps 12, 36 and 60, residents are receiving the relief funds. Around 230 out of 300 residents received the relief funds in 6 years (72 steps) in scenario 2.

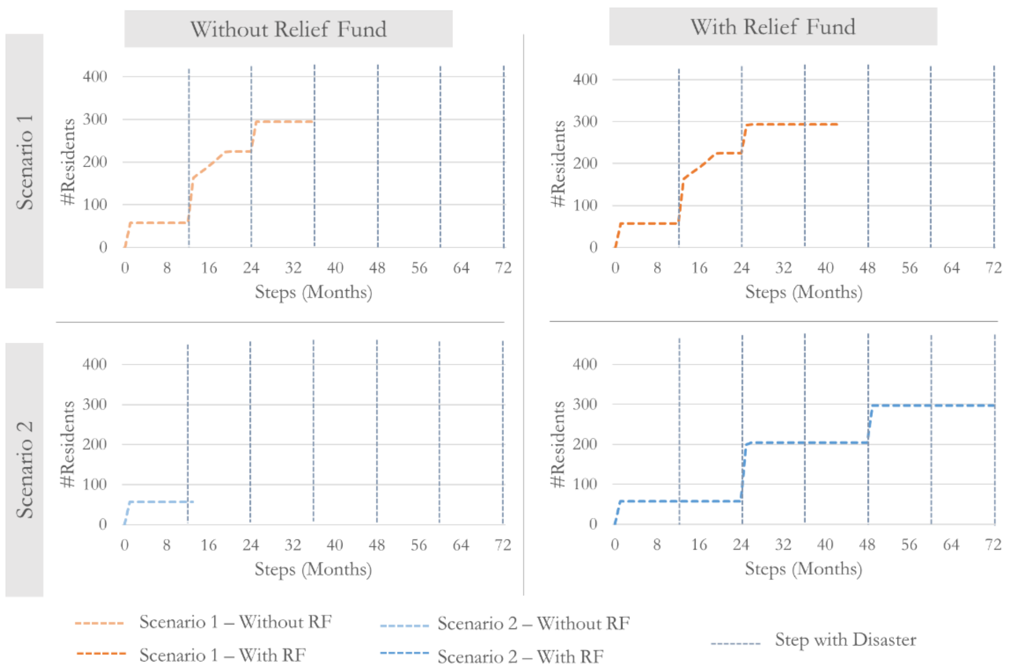


Figure 18 Number of residents receiving the loan overtime for scenarios 1 and 2 - with intervention

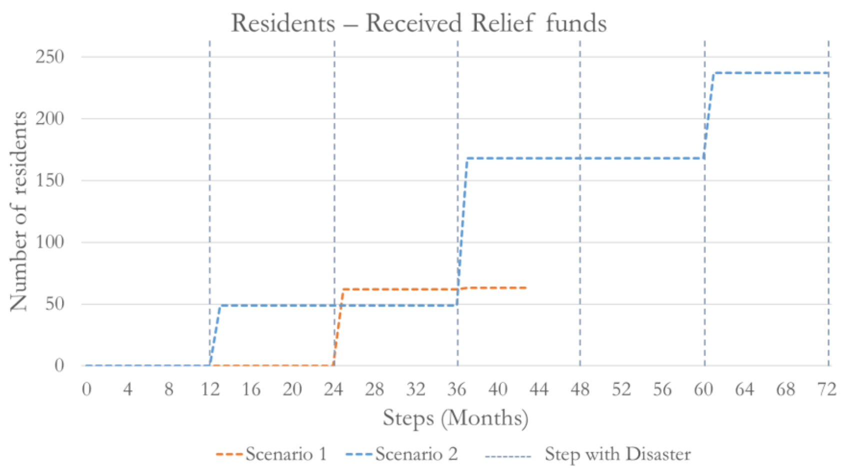


Figure 19 Number of residents receiving relief funds overtime for scenarios 1 and 2 – with intervention

<u>Beneficiaries of the relief-funds – Poor or well off?</u>

As scenario 2 has a larger number of relief funds, this section is explained only with the help of scenario 2. Figure 20 suggests, as the preference is given to the poor, poor are getting the relief-funds before the well-off at step 36. When the preference is given to the poor, they receive the relief fund earlier as compared to well-off.

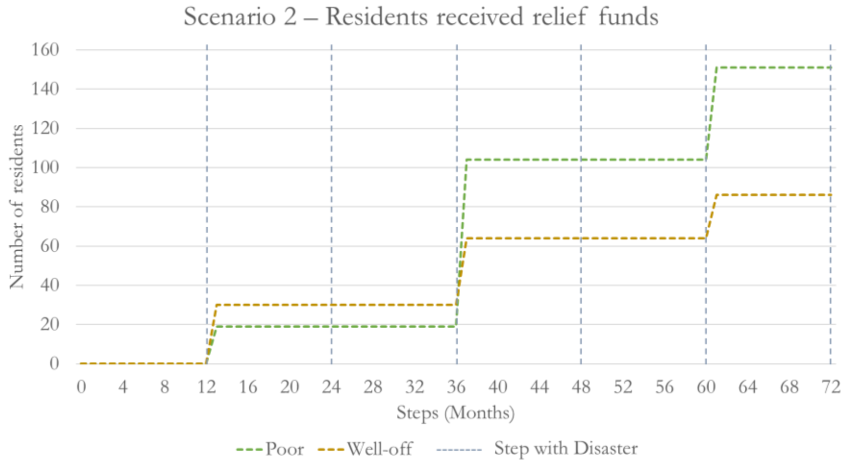


Figure 20 Number of residents receiving the relief-funds with respect to their status for scenario 2

5.1.3.3. Residents owning a business – with intervention in case of a disaster

It is evident from Figure 21, a larger number of residents have owned the business by the end of the simulation in scenario 1 as compared to scenario 2. Almost all the residents in scenario 1 have owned the business whereas around 230 residents (76%) have owned the business in scenario 2. For scenario 1, at every 12th step, the residents are owning the business. Moreover, few residents are also owning the business in between 24th and 36th step. These residents are the one who has received the relief funds from MFI at 24th step. For scenario 2, the residents are owning the business only after first 2 years, i.e. at the 24th step. Thereafter, residents own the business at 48th and 72nd step.

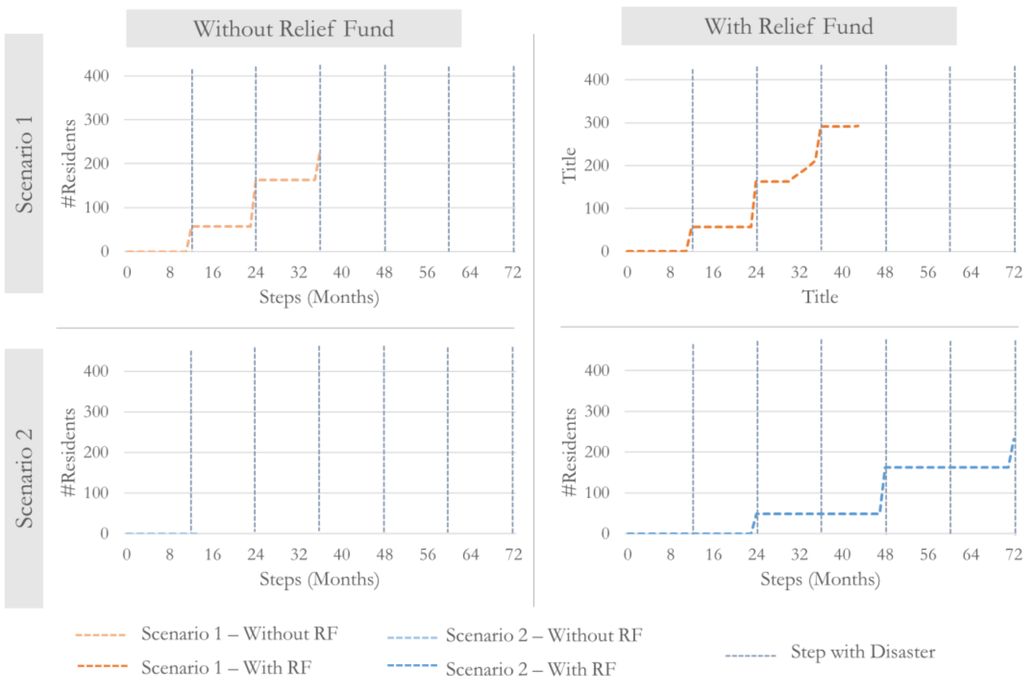


Figure 21 Number of residents owning the business overtime for scenarios 1 and 2 – with intervention

Apart from this, it can also be noted that the provision of relief funds is allowing more residents to own the business for both scenarios. For scenario 2, the provision of relief funds has changed the output of the number of residents owning the business from zero to 76%. For scenario 1, the provision of relief funds has enabled almost all the residents to own the business. Therefore, the adaptive capacity of all the residents has been increased if the relief funds are provided in scenario 1. Moreover, a considerable number of residents have been able to increase their adaptive capacity in case of scenario 2.

5.1.3.4. Defaulters – with intervention in case of a disaster

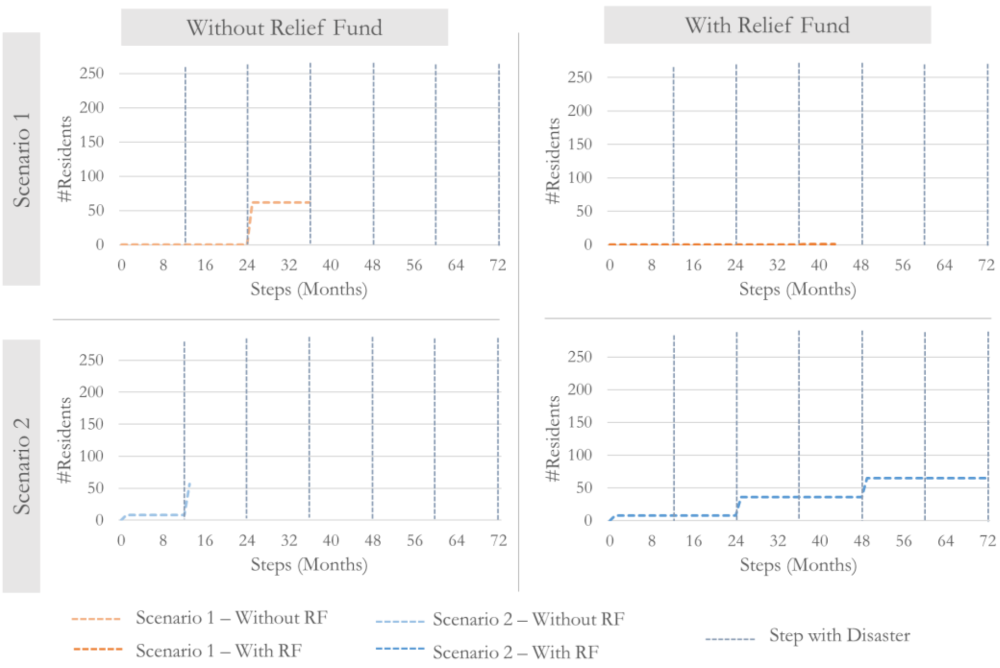


Figure 22 Number of defaulters for scenarios 1 and 2 – with intervention

The defaulters, in this case, can be defaulters for three reasons, namely; inability to repay the loan, did not receive the relief funds or needed a relief fund once more. According to Figure 22, there are more defaulters observed in scenario 2 as compared to scenario 1 when relief funds are provided. Scenario 1 has an almost negligible number of defaulters. If the reason for these defaulters is further investigated, from Figure 23, it is evident that the defaulters are mainly due to the inability of a few residents to repay. There are few defaulters also observed because residents needed the relief funds for the second time at 48th step. This is observed as few residents received the loan between step 24 and 36 imply that the scheduled repayment period will allow them to own the business after the 48th step. As they face a disaster at 48th step, they need the relief fund once more. However, there is no defaulter observed because of not receiving the relief funds suggesting that MFIs had enough funds at the time of disasters.

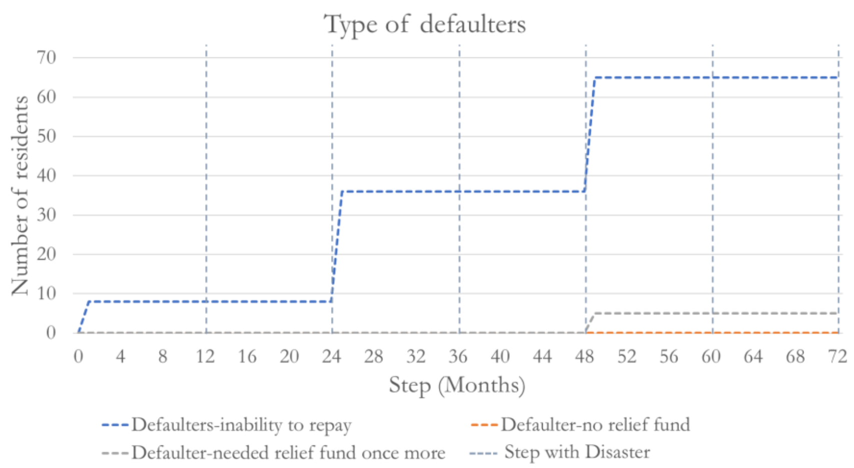


Figure 23 Types of defaulters over time for scenario 2 – with intervention

In scenario 1, the defaulters are almost negligible but are only because these residents needed the relief funds for the second time. These are the residents who received the loan after 18th step and faced 2 disasters while they were repaying the loan.

5.1.3.5. Average productivity - with intervention in case of a disaster

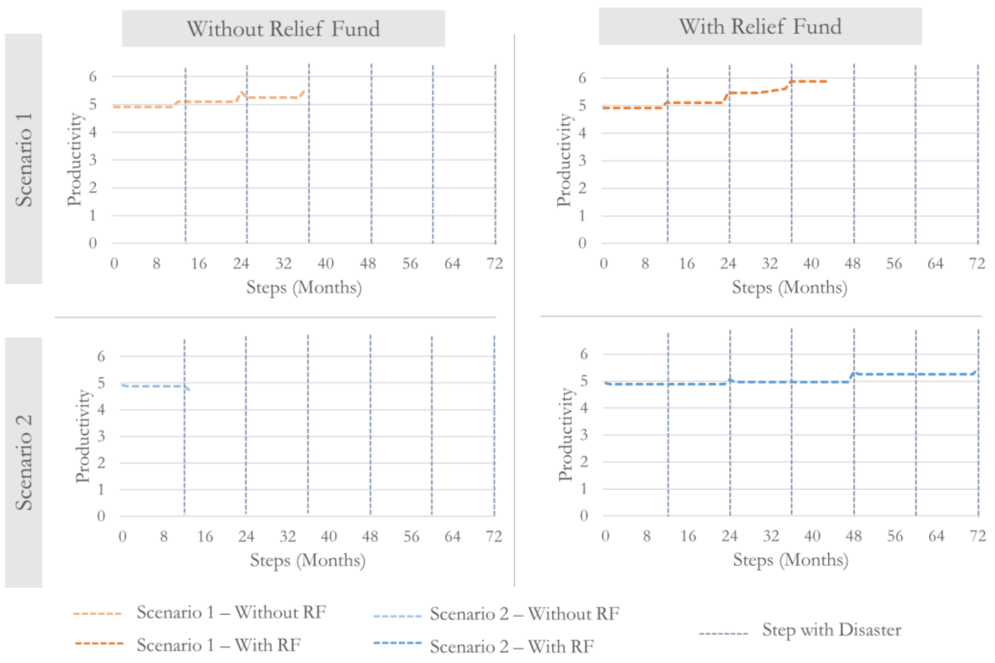


Figure 24 Average productivity over time for scenarios 1 and 2 – with intervention

From Figure 24, it is evident that the average productivity is increasing gradually for both the scenarios. However, at certain steps in scenario 2, the average productivity is observed to be slightly decreasing. This is because of the defaulters observed at this step. Therefore, the average productivity is higher for scenario 1 as compared to scenario 2 by the end of the simulation.

Apart from this, if the relief funds are provided, it is observed to benefit in both the scenarios as the final average productivity is higher in both the scenarios with relief fund as compared to without relief funds. This means that the intervention has aided in increasing the adaptive capacity of residents in the settlement.

5.1.3.6. Funds with MFI - with intervention in case of a disaster

It is evident from Figure 25, that in scenario 2, MFI earns larger amount of money by the end of the simulation as compared to scenario 1. This is because of 2 reasons, namely; the higher interest rate and a greater number of relief funds that were provided. However, if both the scenarios are compared at the end of scenario 1, the funds with MFI are almost comparable. At almost every step of disaster, in both the scenarios MFIs have enough funds to provide for the residents who are wanting the relief funds.

It is clear that the provision of relief funds is beneficial in getting the returns to MFI as more residents are able to repay the loan when compared to the scenarios without relief funds.

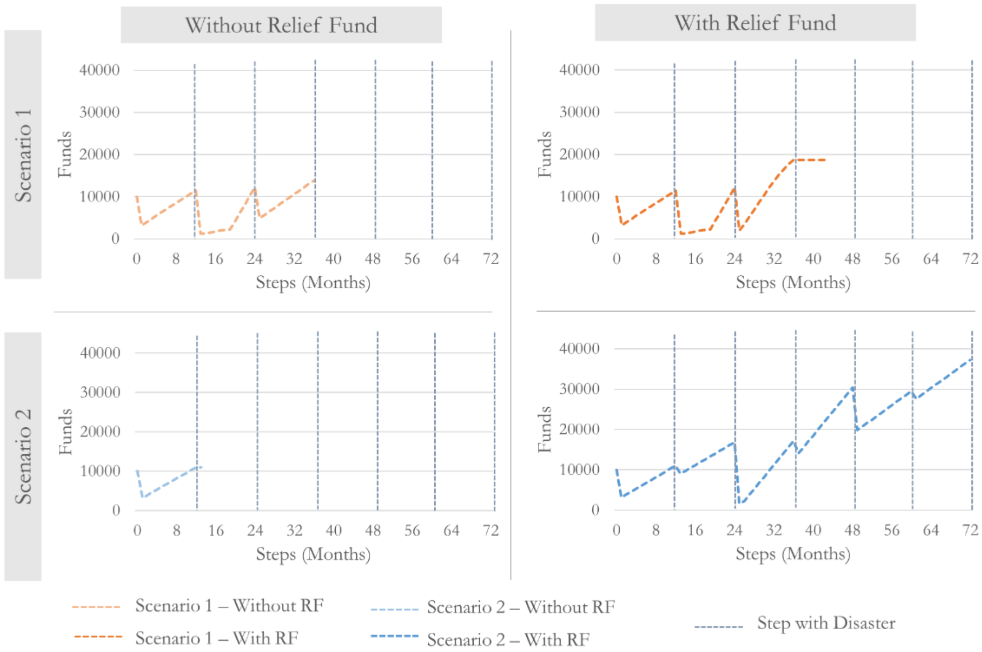


Figure 25 The funds with MFI over time for scenarios 1 and 2 – with intervention

5.2. Sensitivity analysis

This section answers the third research question of the third objective of the study which is –

"How is the model output changing with the change in input parameters?"

This research question is answered with the help of sensitivity analysis as explained in chapter 3.

Table 11 and Table 12 is a compilation of regression results of each output for all the 9 predictors. It provides the favourable value of each predictor corresponding to the favourable value of output. The optimal value of predictor is based on the relationship of the predictor with the favourable value of the output (Refer to Table 4). The negative or positive sign of Beta values suggests whether the predictor has a positive or negative relationship with the output. For example, in case of the output of residents owning the business, the amount of loan has a negative relationship with the output (Refer Appendix II – Table 17). As explained in chapter 3, Table 4, the number of residents owning the business should be larger in an ideal situation. Therefore, owing to the negative relationship with the output, a decrease in the amount of loan will result in an increase in the number of residents owning the business. Apart from this, the table also provides the relative level of importance of predictors which is based on the absolute value of Beta. Moreover, whether the predictors are significant or not is also shown in the table which is based on the significance (Sig.) in all the tables in Appendix II.

5.2.1. Sensitivity Analysis for Simulations without Disaster

According to Table 11, all the outputs have an R square value of around 0.5 or larger. Therefore, a variance of 50% at least in all the outputs can be explained by the predictors mentioned in the table.

To begin with, as shown in Table 11, all the predictors are significant in predicting the number of residents with owned business. Amongst all factors, 'amount of loan' appears to be the most important, followed by 'repayment period', 'interest rate', 'number of residents getting influenced', 'number of residents wanting loan initially', 'initial funds with MFI' and 'preference to the poor'. A decrease in the amount of loan, an increase in the repayment period, a decrease in interest rate, an increase in the number of residents getting influenced and wanting the loan initially, an increase in the initial funds with MFI and preference were given to the poor, resulting in larger number of residents with owned business.

Table 11 Regression results for simulations without disasters

Output	*Optimal Value*	R^2		*Initial Funds*	*Amount of Loan*	*Residents Wanting loan*	*Repayment Period*	*Preference loan provision*	*Residents getting Influence*	*Interest Rate*
Residents owning business	↑	0.575	**Opt. Value**	↑	↓	↑	↑	↑	↑	↓
			Imp.							
Defaulters	↓	0.482	**Opt. Value**	↓	↓	↓	↑	↓	↓	↓
			Imp.							
Time taken by simulation	↓	0.569	**Opt. Value**	↑	↓	↑	↓		↑	
			Imp.					-		-
Avg. Productivity	↑	0.612	**Opt. Value**		↓		↑		↑	↓
			Imp.	-		-		-		
Avg. time taken for loan	↓	0.619	**Opt. Value**	↑	↓	↑	↓	-	↑	
			Imp.					-		-
Avg. time taken for business	↓	0.738	**Opt. Value**	↑	↑	↑	↓		↑	↑
			Imp.					-		
Funds with MFI	↑	0.916	**Opt. Value**	↑	↑		↑		↓	↑
			Imp.			-		-		

Legend

Increase	Decrease	Higher to lower influence
↑	↓	

The order in which the predictors are influencing is slightly different in case of the output of a number of defaulters. The predictor of initial funds with MFI is observed to be more important in case of a number of defaulters as compared to the number of residents owning the business. Moreover, the optimal values for predictors such as; initial funds with MFI, residents wanting the loan initially, preference to the poor, and number of residents getting influenced are opposite to those observed in the output of the number of residents owning the business.

Unlike the previous 2 outputs, the output of time taken by simulation to stop has only 5 significant predictors. Moreover, the order of influence is different from the earlier outputs. The most important predictor is a number of residents wanting the loan initially followed by a number of residents getting influenced. The predictor of the amount of loan is observed to have a lower influence as compared to previous outputs. However, the optimal values are similar to the output of a number of residents owning the business.

For the output of average productivity, only 4 predictors are significant in predicting the output. The results regarding the optimal value are similar to the output of a number of residents owning the business. Moreover, the level of importance of these variables also corresponds with those of the output- number of residents owning the business.

Similar to the output of time taken by simulation to end, the output of average time taken by residents to receive the loan also has 5 significant outputs along with similar optimal values of the predictor. Moreover, the level of importance is also similar to the predictors of the output of the average time taken by the simulation to end. However, the predictors of 'repayment period' and 'number of residents getting influenced' are interchanged in terms of the level of importance.

The output of average time taken by the residents to own the business has an additional predictor of 'interest rate' which is significant as compared to the output of average time taken by the residents to receive a loan. However, other than 'interest rate' and 'amount of loan', all other significant predictors have similar optimal value as seen in the previous output. Along with other significant predictors, higher interest rates and a larger amount of loan are resulting in the shorter time taken by residents to own the business.

The output of funds with MFI also has 5 significant predictors but are not the same as any of the previous outputs. The predictors of 'initial funds with MFI' is the most important predictor, followed by 'interest rate', 'repayment period', 'number of residents getting influenced' and 'amount of loan'. Larger initial funds with MFI, along with higher interest rates, longer repayment period, lower number of residents getting influenced and a larger amount of loan are resulting in larger funds with MFI.

5.2.2. Sensitivity Analysis for Simulations with Disasters

Table 12 Regression results for simulations with disasters

Output	*Optimal Value*	*R²*		*Initial Funds*	*Amount of Loan*	*Residents Wanting*	*Repayment Period*	*Preference loan*	*Residents getting*	*Interest Rate*	*Frequency Disaster*	*Relief -funds*
Residents owning business	↑	0.449	**Opt. Value**	↑	↓	↑	↑	↑	↑	↓	↓	↑
			Imp.									
Defaulters	↓	0.295	**Opt. Value**	↓	↓	↓	↑	↓	↓	↓	↓	↑
			Imp.									
Time taken by simulation	↓	0.576	**Opt. Value**	↑	↓	↑	↓	-	↑	-	↓	↓
			Imp.									
Avg. Productivity	↑	0.436	**Opt. Value**	↑	↓	↑	↑	↑	↑	↓	↓	↑
			Imp.									
Avg. time taken for loan	↓	0.656	**Opt. Value**	↑	↓	↑	↓	↑	↑	↓	↓	↓
			Imp.									
Avg. time taken for business	↓	0.662	**Opt. Value**	↑	↑	↑	↓	↑	↑	↑	↓	↓
			Imp.									
Funds with MFI	↑	0.904	**Opt. Value**	↑	↑	↓	↑	↓	↓	↑	↑	↑
			Imp.									

Legend

Higher	Lower	Importance: Higher to lower
↑	↓	

The R square values, if compared to the sensitivity analysis without the disasters, are lower. For outputs of residents owning the business, defaulters and average productivity the R square values are much lower than the values observed in the previous section. However, for outputs of time taken by simulation and average time taken by residents to receive the loan the R square values are higher.

Model inputs of 'frequency-disaster' and 'relief funds' are added in the regression analysis as two additional predictors. Adding these predictors have not changed the relationship of other predictors with the output. However, the level of importance has slightly changed. The most evident change can be seen in the results of outputs of average productivity, the average time taken by the residents to receive the loan and own the business and funds with MFI at the end of the simulation. In the previous section, few predictors for these outputs were not significant, whereas in this case, all the predictors including the predictors related to disaster are also significant. For all the outputs except for funds with MFI, if the frequency of disasters is low, the output is favourable. However, with the provision of relief funds, only the outputs of residents owning the business, the number of defaulters, average productivity and funds with MFI at the end of the simulation are having optimum values. Other outputs are not desirable if the relief funds are not provided.

5.2.3. Synopsis of sensitivity analysis

The sensitivity analysis suggests that the repayment period is one of the most important predictors for all the outputs. Moreover, an increase in the value of repayment period results in a few of the outputs to be favourable whereas few of the outputs are only favourable if the repayment period is shorter. Subsequently, the amount of loan also is observed to be an important predictor, and a decrease in the amount of loan is suitable for most of the outputs. Apart from this, the provision of relief funds has been useful for four of the outputs. For most of the outputs to be optimal, an increase in the number of residents wanting the loan initially along with an increase in the number of residents getting influenced by successful residents is leading to favourable outputs. Moreover, an increase in initial funds with MFI along with the preference given to the poor results in favourable outputs.

Table 13 Values of model inputs based on the sensitivity analysis

S. No	Model Input	The result of Sensitivity Analysis: Optimal values of predictors	Values
1	Funds with MFI	Increase	50,000
2	Amount of loan	Decrease	50
3	Number of residents wanting the loan initially	Increase	150
4	Repayment Period (Most Important)	Decrease for some outputs & Increase for some outputs	12, 14, 16
5	Preference?	Preference given to the poor	Yes
6	Number of residents getting influenced	Increase	5
7	Interest rate	Decrease	20
8	Frequency of disaster	Decrease	Once in 5 years
9	Relief funds?	Provided	Yes

Table 13 is generated with optimal values of all the predictors with reference to the results of sensitivity analysis. If the sensitivity analysis suggests an increase in the value of predictor provides favourable results, the optimal values are considered to be largest value amongst the values mentioned in Table 3. For example, the favourable values of initial funds with MFI is considered to be 50,000 (highest value) amongst the values that can be varied for the predictor.

Sensitivity analysis suggests that if the frequency of disaster is decreasing, most of the outputs are favourable. However, there is a need to investigate whether the values of predictors are favourable in case of higher frequency of disaster. Moreover, sensitivity analysis suggests that the repayment period is the most important predictor and as per Table 13, 3 values can be further investigated to identify the optimal value. Therefore, the scenarios with a repayment period of 12, 14 and 16 are presented in the section below. Apart from this, sensitivity analysis also suggests that the number of residents wanting the loan initially and the number of residents getting influenced are also important for most of the outputs. Therefore, they are also investigated further in this section. Additionally, funds with MFI is observed to be important in reality, whereas in the sensitivity analysis it is observed to be the least important. Therefore, this section investigates this further.

5.2.3.1. Scenarios with a repayment period of 12, 14 and 16 months

Based on the values of predictors in Table 13, a number of residents that are owning the business was plotted against the frequency of disasters. The simulations with the values in the table were also tested for 3 repayment periods as it is the only predictor that has few simulations with a larger value as favourable and few simulations with smaller value as favourable. From Figure 26, it is evident that for the frequencies of once in two years and so on, the number of residents owning the business is same for all the frequencies of disaster and all the repayment periods except when the frequency of disaster is once a year and repayment period is 14.

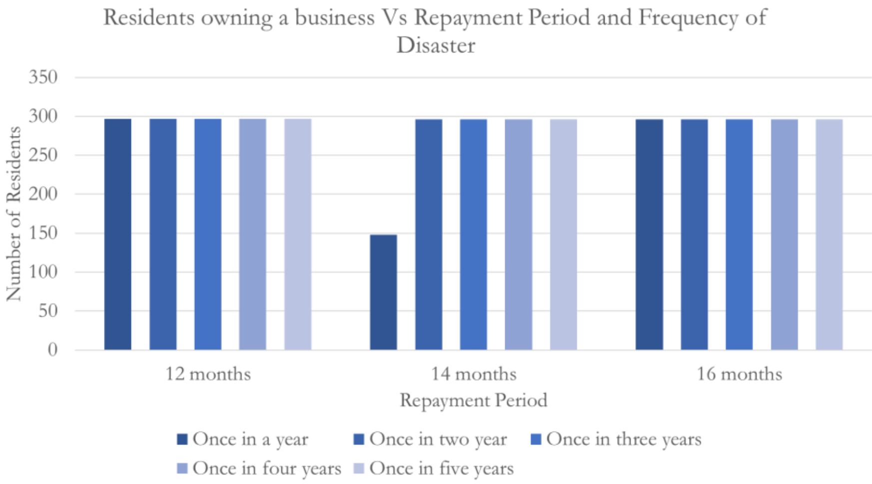


Figure 26 Number of residents that have owned the business with respect to the frequency of disaster and repayment period

Figure 27 suggests that the time taken by simulation is the same when the repayment period is 12 for all the frequencies of disaster. In this situation, it can also be noted that the time taken by the simulation is the smallest, i.e. around two years, in case of repayment period as 12 months. However, for the repayment period of 14 months, the time taken when the frequency of disaster is once a year is longer and the number of residents owning the business is also lower. Furthermore, the time taken by the simulation is around 3 years when the frequency of disaster is once in two years. However, for further frequencies, the time taken is almost the same as the process ends before the disaster, i.e. within 2 years. The time taken by the simulation is the longest for repayment period of 16, however, for frequencies of disasters less than once in three years, it is less than 3 years as simulation ends before the occurrence of a disaster.

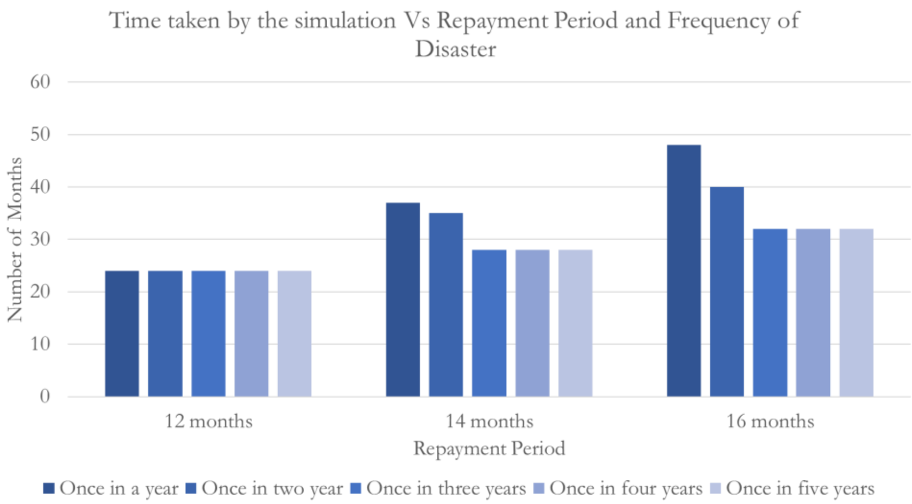


Figure 27 Time taken by simulation with respect to the frequency of disaster and repayment period

To understand the reason behind the result of the repayment period of 14 months, 3 simulations with settings as mentioned in Table 14 were investigated.

Table 14 Values to investigate the pattern of residents owning a business over time for three repayment periods (12, 14, 16)

Initial funds	Residents wanting loan	Amount of loan	Repayment period	Residents getting influenced	Preference	Interest rate	Relief fund	Frequency
50000	150	50	12, 14, 16	5	To the poor	20	Provided	Once a year

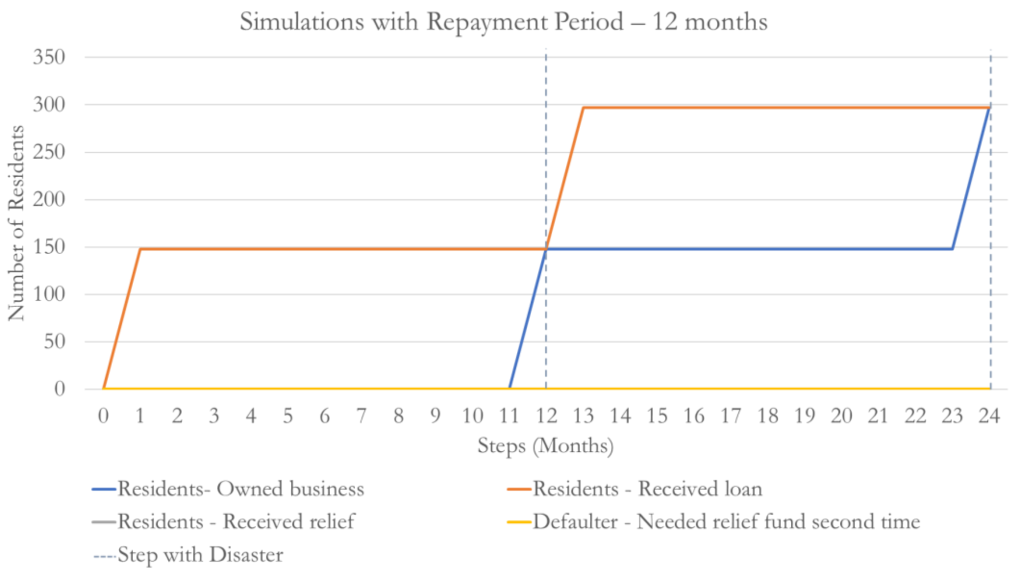


Figure 28 Output when repayment period = 12, disaster frequency = one per year

As seen in Figure 28, almost all the residents that have received the loan have owned the business. As most of the residents that have received the loan are owning the business before the disaster, there are no relief funds required by the residents (see steps 12, 24).

Similarly, in Figure 29, with a repayment period of 16, all the residents that have received the loans are able to own a business. However, in this case, there is a need of relief fund at 12th, 36th and 60th step as the repayment period is 16 suggesting that the residents that have received the loan before these steps are still in the process of repaying the loan. After receiving the relief funds, the rescheduled repayment period is 24 implying that the residents are able to pay the loan before the next disaster.

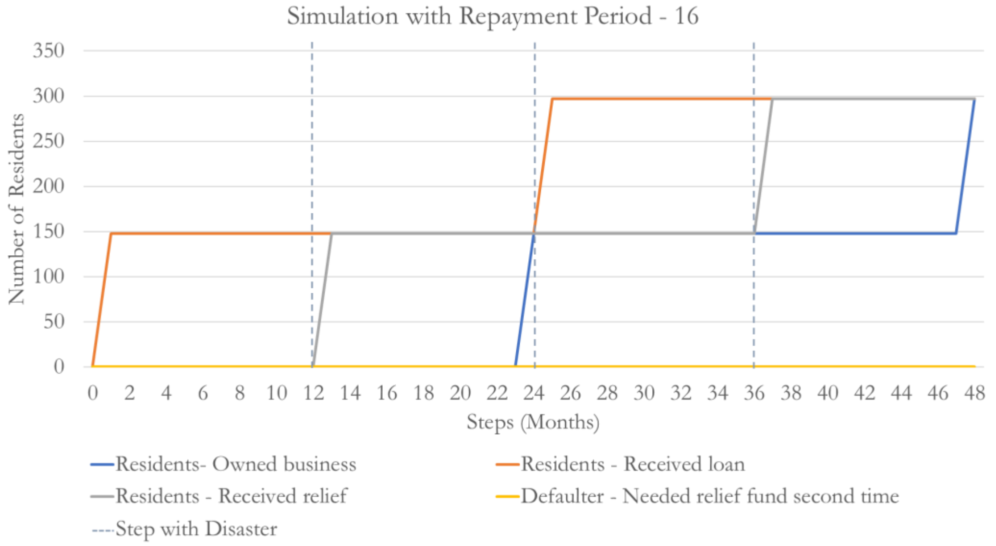


Figure 29 Output when repayment period = 16, disaster frequency = one per year

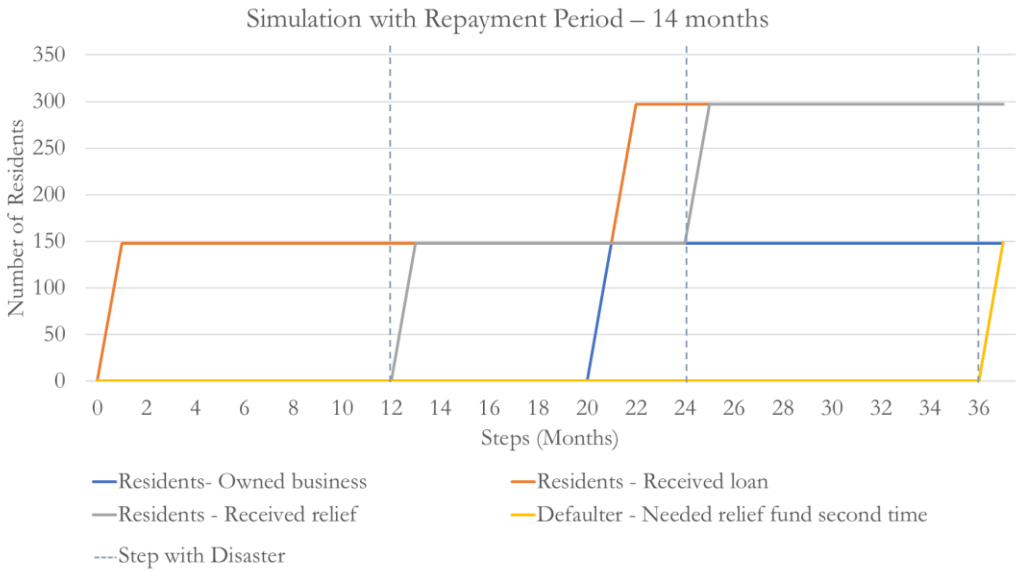


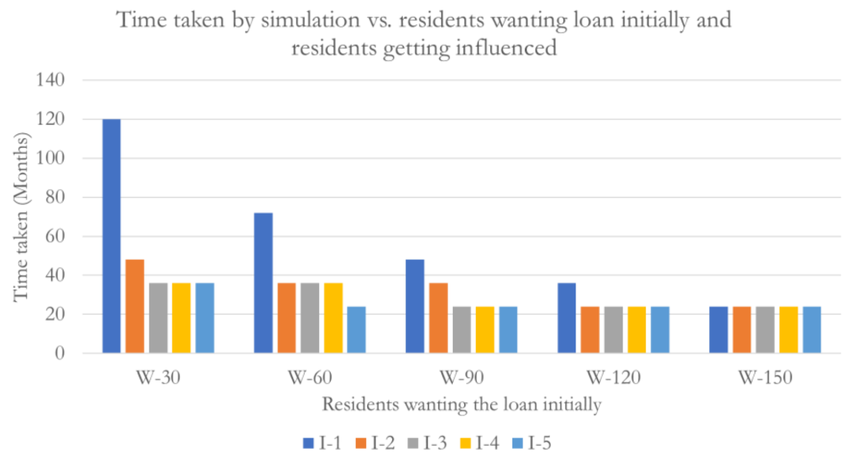
Figure 30 Output when repayment period = 14, disaster frequency = one per year

On the contrary, with the repayment period of 14, not all the residents who have received a loan are able to own the business resulting in defaulters (refer Figure 30). Moreover, the MFI has also provided the residents with relief funds at steps of 12 and 24 which are corresponding to the events of disaster. As the revised repayment period, in this case, is 21 months, the residents that received the loan initially, with the help of relief funds during the first occurrence of a disaster, owned the business at 21st step. At this step, the residents that were influenced received the loan at the very next step. Due to a disaster at 24th step, all the residents that received the loans, needed a relief fund to own the business. Till the disaster at 36th step, the residents could only repay the loan for 15 months and as they were still in the process of repaying needed another relief fund. As MFI provides the relief fund only once in the model, these residents were, therefore, unable to repay the loan and became defaulters.

If the repayment period is 12 or 16 when the frequency of disaster is once per year, almost all the residents can own the business. They faced the disaster twice in process of repayment in case of the repayment period of 14 months because they received a loan less than three months before the disaster.

5.2.3.2. Scenarios with varying values of 'residents wanting the loan initially' and 'residents getting influenced'

In reality, not many people are aware initially about the provision of microcredit services. Moreover, the number of residents that are getting influenced by successful residents cannot be gauged. Therefore, the influence of these two input parameters is tested with the help of values from Table 15.



I-1 – 1 resident getting influenced by each successful resident; **W-30** – 30 residents want the loan initially

Figure 31 Time taken by simulations for various values of 'residents wanting the loan initially' and 'residents getting influenced'

Table 15 Values to investigate the influence of 'number of residents wanting the loan initially' and 'number of residents getting influenced'

Initial funds	Residents wanting loan	Amount of loan	Repayment period	Residents getting influenced	Preference	Interest rate	Relief fund	Frequency
50000	30, 60, 90, 120, 150	50	12	1, 2, 3, 4, 5	To the poor	20	Provided	Once a year

In all the simulations produced with the values mentioned in Table 10, the number of residents that have owned the business is around 90% or above. From Figure 31, it is observed that, if the number of residents getting influenced is 3 or above, almost all the residents are owning the business within 3 years or less in all the simulations, irrespective of the number of residents wanting loan initially. Moreover, if the number of residents wanting the loan initially is 30% (90) or above, almost all the residents are owning the business within 4 years or less in all the simulations, irrespective of the number of residents getting influenced in the process. However, if the value for residents getting influenced and residents wanting the loan initially are 1 and 60 or less respectively, then the time taken by simulations is more than 6 years.

5.2.3.3. Scenarios with varying values of 'initial funds with MFI'

The simulations are varied according to the values given in Table 16. As discussed in the previous section, as the residents wanting the loan initially are not many, a value of 60 is used in this case. Moreover, in this study amount of loan is just related to the ability to repay. Sometimes, larger loans are required to start the business properly. Therefore, the amount of loan is considered to be 100 to present the cases where the requirement of funds might be relevant.

Table 16 Values to investigate the influence of 'initial funds with MFI'

Initial funds	Residents wanting loan	Amount of loan	Repayment period	Residents getting influenced	Preference	Interest rate	Relief fund	Frequency
5000, 10,000, 20,000, 50,000	60	100	12	5	To the poor	20	Provided	Once a year

From Figure 32, it is evident that the residents who want the loan in case of initial funds 5000 and 10,000 are waiting to receive the loan. At the 12th step, not all the residents that are wanting the loan are receiving the loan in case of initial funds with MFI 5000 and 10,000. It is evident that residents are receiving the loan between the 12th and 24th step. On the other hand, the scenarios with initial funds with MFI as 20,000 and 50,000, all the residents that want the loan are immediately receiving the loan in the same step.

From Figure 33, it is evident that when the initial funds with MFI are 5000, at 24th step, around 20 residents are receiving the relief funds whereas around 50 residents are not receiving the relief funds. In the cases where initial funds with MFI are greater than or equal to 10,000, almost all the residents that need relief funds are receiving the relief funds.

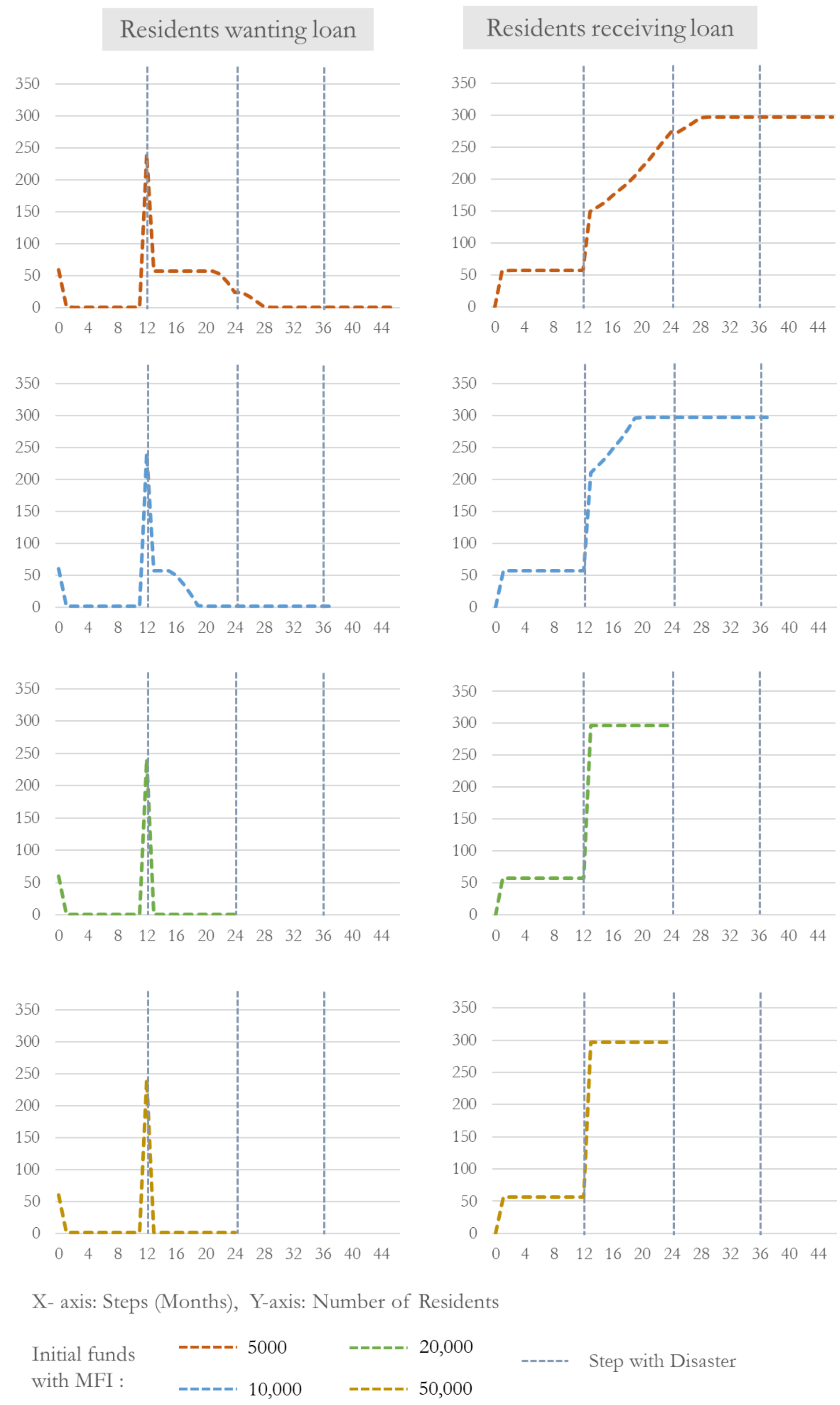


Figure 32 Number of residents wanting and receiving loans for different values of initial funds with MFI over time

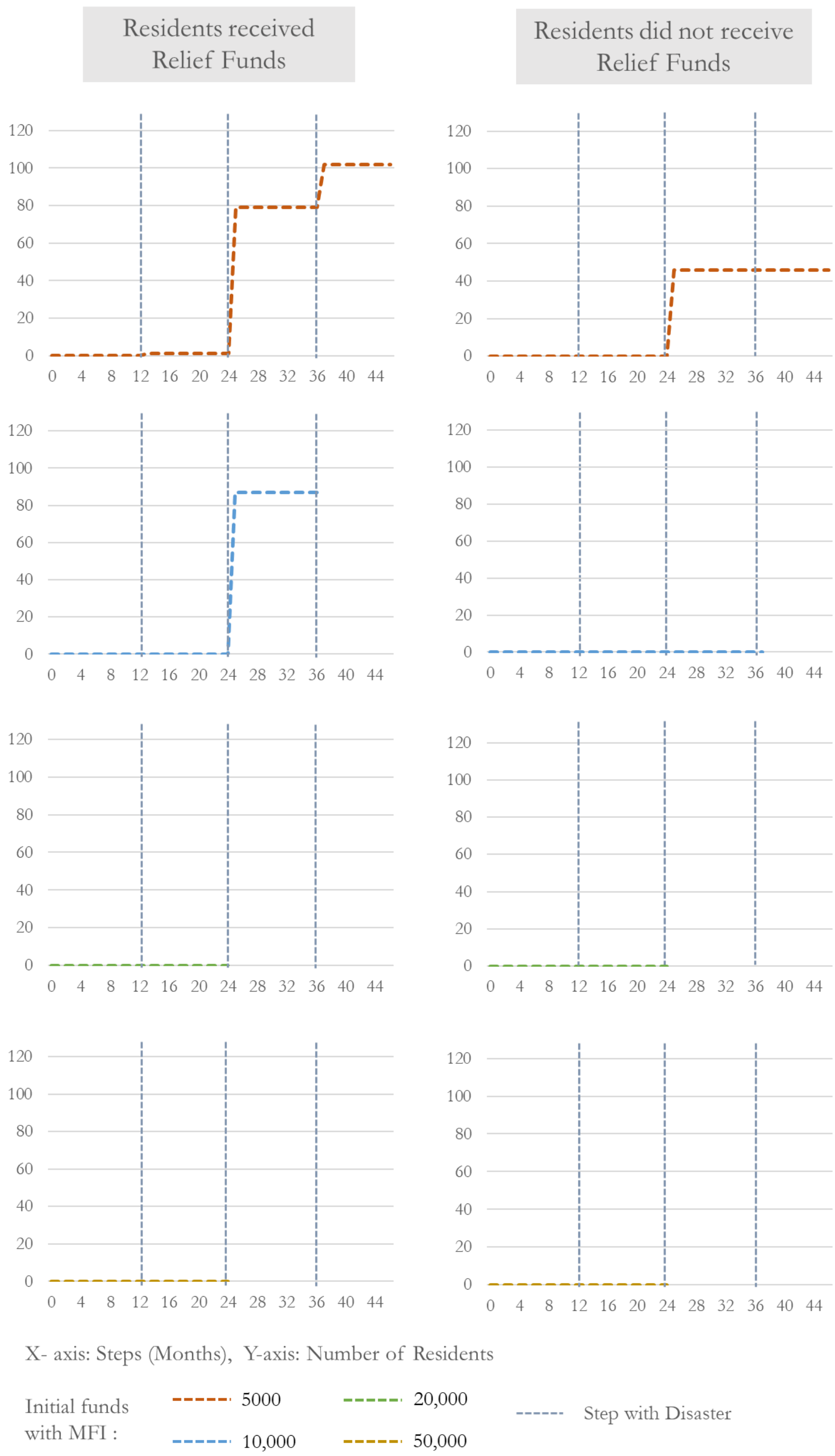


Figure 33 Number of residents that did not receive relief funds for different values of initial funds with MFI over time

6. DISCUSSION

This chapter discusses the results presented in the previous chapter. The first section of the chapter deliberates upon the sensitivity analysis of the model followed by strengths and limitations of the model.

6.1. Discussion – Sensitivity Analysis

This section discusses the results of the sensitivity analysis. In the first part of this section, an overview of the results of the sensitivity analysis is given by discussing the changes in R square values and the insignificance of predictors. The second part of this section discusses the influence of predictors on the model outputs in case of disasters and when the intervention of relief funds and restructuring of the repayment period is provided.

6.1.1. Change in R square values and Insignificance of Variables

The R square values of outputs without the disaster are reducing when two predictors – disaster frequency and relief fund are added. Although the dataset is different for both the sensitivity analyses, the R square values can be compared to an extent as the dataset is too large (around 200,000 observations). In general, with the addition of predictors, R square value improves; however, in this case, it has reduced. The reason could be that the added predictors are affecting the influence of other predictors on the output. For example, the provision of loans for longer repayment period in case of frequent disasters might lead to defaulters as residents need more relief funds. Moreover, if the frequency of disaster is once in 5 years, a relief fund is not relevant as the simulation ends before the disaster. This also suggests that the predictor of relief fund is relevant only in case of higher frequency of disaster. Such a phenomenon is termed as "Interaction Effects" in statistics (Jaccard & Turrisi, 2003).

The insignificance of few predictors in some of the outputs can also be explained with the above phenomenon. One of the other reasons behind the insignificance of a predictor could be multi-collinearity. However, none of the variables is collinear each other in any of the cases according to the tolerance and VIF values (Refer Annexure I). There are other tests also to detect multicollinearity, however, they are not explored in this study due to limited time.

6.1.2. Influence of Predictors on Model Outputs

In this section the influence of each predictor on model outputs is discussed in detail.

6.1.2.1. Influence of Initial funds with MFI on model outputs

In principle, larger funds with MFI ensures higher accessibility of residents to loans (Caserta, Monteleone, & Reito, 2018). The results of sensitivity analysis are in line with this as they suggest that the increase in the initial funds with MFI leads to favourable outputs. However, in the results, it is also observed that an increase in initial funds with MFI also results in an increased number of defaulters. The reason behind this could be the increase in the number of residents that are receiving the loans with an increase in initial funds with MFI. All the residents that have received the loan have a probability to become a defaulter or to own a business. Apart from this, initial funds with MFI are having lower influence as compared to other predictors. The reason for this could be that the values of initial funds with MFI considered in the model are adequate for the situation. Section 5.2.3.3 suggests that there is a need for additional funds for MFIs in case of a lower value of initial funds with MFI. As mentioned by Becchetti and Castriota (2011) the need for additional funds which is named as the recapitalisation of MFI has been proven useful in case of disasters.

6.1.2.2. Influence of Amount of loan on model outputs

According to the sensitivity analysis, a decrease in the amount of loan results in most of the outputs to be favourable. However, a decrease in the amount of loan also results in a longer time taken by residents to own the business. This is because this output considers only the number of residents that have owned the business. In the cases where the number of residents that have owned the business is lower, the output will have a lower value if all of them are owning a business within lesser time.

A smaller amount of loans are mostly received by the poor as they are able to repay it (Dorfleitner, Priberny, & Röhe, 2017). However, the loans that are demanded by residents vary from smaller to larger amounts depending upon the purposes (Bhole & Ogden, 2010). As the model assumes that all the amounts of the loan are enough to start a business, this predictor only accounts in the repayment ability and not the ability to do a good business. Therefore, although larger amounts of loan might help develop a successful business, the result suggests a smaller amount of loan as favourable as it accounts only for an individual's or group's ability to repay.

6.1.2.3. Influence of Number of Residents Wanting a Loan Initially on Model Outputs

According to the sensitivity analysis, an increase in the number of residents initially wanting a loan results in favourable outputs. However, it also results in an increase of defaulters and decrease in final funds with MFI. The reason behind this could be an increase in the number of residents receiving the loan in this scenario. Therefore, as mentioned earlier, there is an equal probability of owning the business as well as becoming a defaulter. Similarly, if the number of defaulters is large in this case, funds with MFI at the end of the simulation will not be higher.

In reality, MFIs struggle initially to have a substantial outreach in poverty-ridden areas and therefore, do not witness a lot of residents applying for these loans in the initial stages (Massele & Fengju, 2016). According to the sensitivity analysis, an increase in the number of residents wanting the loan initially is beneficial for the MFIs in terms of outreach as these successful residents later influence other residents in the region to avail these loans. However, it might add to the information and transaction costs of MFIs and result in an increased cost of loans. The model, however, does not incorporate this process.

6.1.2.4. Influence of Repayment Period on Model Outputs

As mentioned in the results, the repayment period is observed to be one of the most important predictors for all the outputs. The sensitivity analysis suggests that an increase in the repayment period increases the number of residents owning the business, whereas it also increases the time taken by all the residents to own the business. However, this result is in line with the literature review which mentions that a longer repayment period, is a facility for residents as the amount of instalment is small and payable for each month (Mokhtar et al., 2012). However, a longer repayment period might not be beneficial for MFIs if they are wanting to provide the service for a shorter amount of time. Moreover, if the repayment period is longer in case of frequent disasters, the MFIs might have to provide a greater number of relief funds per resident as shown in section 5.2.3.1.

6.1.2.5. Influence of Preference on Model Outputs

According to the literature review, MFIs do not prefer the poor for the provision of a loan as they do not have the credibility to repay the loan. However, due to the provision of group loans, the poor with the help of their peers manage to repay the loans (E. Field & Pande, 2012). In general, if the intervention of microfinance has to be effective for the poor, the poor should be preferred by the MFIs as it will enhance the outreach of MFIs (Caserta et al., 2018). According to the sensitivity analysis, if a preference is given to the poor, most of the outputs are favourable. However, the defaulters are larger in number if the preference is given to the poor. The reason behind this could be that the number of the poor are more than the number of well-off in the model. Also, most of the poor are able to own the business as their ability to repay is based on the group size. The model, therefore, is successful in capturing the fact that group formations are useful in achieving a good repayment rate as mentioned by Lehner (2008).

6.1.2.6. Influence of Number of Residents Getting Influenced by Each Successful Resident on Model Outputs

An increase in the number of residents getting influenced by each successful resident result in favourable outputs in the model according to the sensitivity analysis. As mentioned in the literature review, due to high transaction and information costs, MFIs often choose financial sustainability approach over the poverty lending approach (Hermes & Lensink, 2011). To avoid this, according to Wydick et al. (2011), social networks can be useful. The model correctly represents the effect of spreading awareness through social networks. However, in this case, only the neighbours are getting influenced. If the number of residents getting influenced by each successful resident is higher, a greater number of loans can be given at an early stage with a view to providing a source of income to households as early as possible.

However, similar to the predictor of 'residents wanting the loan initially', an increase in the value of this predictor results in an increase in the number of defaulters and funds with MFI by the end. The reason behind this also is the same as the one given for the predictor of 'residents wanting the loan initially'. Basically, as the number of residents receiving the loan is larger there is an equal probability of the residents owning the business and becoming defaulters in a certain situation. As the number of defaulters is more in this case, the funds with MFI also will be less by the end.

6.1.2.7. Influence of Interest Rate on Model Outputs

An interest rate is observed to be important in a few of the outputs according to the sensitivity analysis. In principle, microfinance services are known to have lower interest rates as compared to local money lenders (Dehejia et al., 2012). Lower interest rates offered by MFIs attract the poor to invest in microcredits. However, as explained in the financial system approach in the literature review, if the costs of running an MFI is higher, MFIs usually give away the loans at higher interest rates (Hermes & Lensink, 2011). To facilitate the poor, in principle, MFIs should have lower interest rates in order to enhance the ability to repay of residents. In this line, the sensitivity analysis suggests that a decrease in interest rates result in most of the outputs to be favourable. However, a decrease in interest rate also result in longer average time taken by residents to own the business. The reason for this could be that the output does not consider the number of defaulters or the number of residents who did not receive the loan as explained above.

Apart from this, if the interest rates are higher, the output of funds with MFI is also higher. This is because of the increase in the amount of instalment. According to the literature review, the interest rate is a crucial element in the functioning of the microcredit service. However, sensitivity analysis suggests that the level of importance of this predictor is not as much as of repayment period. The reason behind this could be the assumption that if the instalment is less than or equal to one-third of the income or combined income of the resident, the resident can repay the loan. This assumption has resulted in most of the residents repaying the loan for even higher interest rates. The residents, in reality, might have lesser repayment ability.

6.1.2.8. Influence of Frequency of Disaster on Model Output

A decrease in the frequency of disasters results in favourable outputs according to the sensitivity analysis. Moreover, if the repayment period is 12 months and if the other values are according to the Table 13, the outputs are favourable in case of the highest frequency of disaster. As this predictor influences other predictors as mentioned above, it is mostly discussed along with the relief funds.

6.1.2.9. Provision of relief funds

Relief funds are provided to aid the residents in case of disaster so that the residents are able to own the business. As discussed in section 6.1.1, the predictor of the provision of relief fund is valid only in case of higher frequency of disasters. As per the sensitivity analysis, the outputs of time taken by a simulation, average time taken by residents to obtain the loan and average time taken by residents to own the business are not favourable if relief funds are provided. This is mainly because the provision of relief funds restructures the repayment period, and additional time is provided to the residents to repay the loan. As not providing relief funds results in a greater number of defaulters, it is logical to say that the provision of relief funds is helpful even if it elongates the process of owning the business.

6.2. Major findings from the Model

This section provides the main findings, lessons learnt, and usefulness of the model in the context of microcredit and disaster in an informal settlement. However, these findings are valid in case of the studies that resemble the situation presented in the model.

1. Most of the residents are receiving the loan and owning the business if the relief funds are provided along with the restructuring of the repayment period. However, as mentioned in the results, if the residents have received the loan less than three months before the disaster, they face the disaster twice in the process of repayment. In this case, relief funds are needed twice and providing the relief fund only once might not be helpful. This result is only valid if the time of disaster is similar every year. Therefore, the model can be useful in understanding the usefulness of intervention of relief funds if the user knows the time of disaster.
2. The model also suggests that the repayment period should be moderately long and should be planned considering the time of disaster.
3. The model also informs the need for recapitalisation of MFIs during the disasters if the funds with MFI at the time of disaster is not enough. As discussed by Becchetti and Castriota (2011), recapitalisation was proven to be helpful in case of a Tsunami of 2004 in Sri Lanka. Therefore, the model can inform the need for recapitalisation by testing different scenarios.
4. The model, as explained above, suggests that influencing the residents using social networks can help increase the outreach of microcredit service. The model redirects the attention to using the social networks for diffusion of information regarding microfinance to an extent.
5. The model also suggests that the formation of groups is useful in repaying the loan. Moreover, it also suggests that the higher interest rates lead to a larger number of defaulters. These results are conforming with the results of Rashid et al. (2011) and Bourhime and Tkiouat (2018). Additionally, this model explicitly includes the role of microcredit service in case of disasters.

6.3. Limitations

This section discusses the limitations of the model in two sections; further model refinement and limitations observed in analysing the model.

6.3.1. Further Model Refinement

The model can be refined mainly with respect to the following points:

1. The model is a stylized model and is developed using the literature review done by the author. Although it helps in understanding the functioning of MFI and usefulness of the intervention of the relief fund, it lacks the backing of empirical data. The model can be refined further with the help of empirical data based in an informal settlement that faces disasters regularly.
2. Furthermore, assumptions related to behaviour and decisions made by the residents that are mentioned in the conceptual framework of the model can be refined further. Moreover, the model can be enhanced by adding the intensity of the disaster as one of the input parameters.

3. The model can also be scaled up by adding more agents such as local leaders and government officials that are involved in disaster management in an informal settlement.
4. The landscape of the model is an informal settlement; however, the population of informal settlement is much higher than the assumed number of residents in the model. The residents in the model are assumed to be one resident per household. However, if the household size is large, a group can be formed within the household to start a business. Such cases can be included in the model for further enhancement.

6.3.2. Limitation in analysing the results of the model

As mentioned above, the reason behind the insignificance of few of the predictors and reduction in R square can be explained with the help of interaction effects. However, due to limited time, this could not be explained in this thesis at length. The interaction effects can be further explained with the help of 'structural equation modelling' (Dilalla, 2000). This could then assist in explaining the relationship between the predictors as explained in section 6.1.

Moreover, there are four main steps to analyse the model mainly; software verification, calibration/parameterisation, validation and answering the research question (Grimm & Railsback, 2005). The study attempts in answering the research question and to an extent address the steps of software verification, calibration/parametrisation and validation. However, due to limited time, performing these steps thoroughly was not possible. The way these steps are addressed is discussed below.

6.3.2.1. Software Verification

The verification of the computerised model is done with the help of NetLogo. As the model is developed using NetLogo which is a special purpose programming language used mainly for agent-based modelling, it has fewer errors than any general-purpose programming language like python. In order to test the simulation models, techniques such as structured walkthrough and correctness proofs can be used (Sargent, 2010). However, in this study, as the results obtained conform to the literature review, the code of the model is assumed to be correct and logical.

6.3.2.2. Calibration/ Parameterization

In this study calibration or parameterisation is not done while developing the model. There were parameters of which the values were unknown. For example, how much from the monthly income can be repaid to the MFI in terms of instalment was unknown. However, an assumption that around one-third of the income can be repaid was considered because of which model produced results such as with an interest rate of 80% most of the agents were able to repay the loan. These results can be true; however, it is often argued that as the residents are unable to afford higher interest rates, MFIs tend to provide microcredits at lower interest rates. A calibration of this value could have enhanced the results of the model. Apart from this, there were no straight forward unknown parameters that could have been calibrated. However, this can be a part of further studies.

6.3.2.3. Validation of the model

As the model is a stylized model, it lacks an empirical backing to it. Now, due to limited time, the model was not validated using any empirical data as such a data was not available. Sargent (2010) describes two types of model validation; conceptual model validation and operational validation. Conceptual model validation focuses on establishing the correctness of the underlying theories and assumptions of the model. The primary validation technique used for this is face validation. Face validation involves evaluation of model or model behaviour with the help of knowledgeable experts in the field. As the conceptual model is developed based on the literature review of the concepts of microcredits and its integration with disaster management, the model is validated in terms of theories and assumptions to an extent. However, a conceptual model validation can be enhanced with the help of discussions with the experts in the field.

Operational validation relates to the accuracy of the model's output behaviour required for the intended purpose of the model (Sargent, 2010). The operational validation can be carried out with the help of several techniques, objectively or subjectively. This study has used a subjective approach to validate the model outputs using sensitivity analysis. Sensitivity analysis explores model behaviour and helps the modeller to understand whether the output of the model is logical. In order to obtain a higher degree of confidence in the model, it is important to validate it effectively, i.e. by comparing it with other existing models or testing it using the empirical data. As there is no other model found which is similar to the model developed in this thesis, the approach of comparison is not possible. The model can be tested using the empirical data in future. Pattern-oriented validation as explained by Grimm and Railsback (2005) explains how well the model has reproduced the patterns in reality. However, this type of validation will also need an expert opinion and a literature review on theories of microfinance.

7. CONCLUSION

This chapter attempts in concluding the research by reflecting on the achieved objectives and providing the scope for future work.

7.1. Reflection on Research Objectives

The study successfully developed a stylized ABM that enabled investigation of the role of microcredit and its intervention in case of disasters in an informal settlement with the help of a literature review. Microcredit service, as mentioned in the literature review, enhances the adaptive capacity of residents. Moreover, the frequency of hazards is also increasing due to climate change. In this line, the study suggests that microcredit service along with its intervention is useful in case of disasters in an informal settlement.

The developed ABM in this study was an attempt to create a simplified version of reality to understand the role of microcredit and its intervention in case of disasters. The model suggested that the intervention of relief funds and restructuring of the repayment period is useful in increasing the number of residents with owned business in case of disasters. However, the model considers that if the resident has owned the business, it will be able to combat the effects of disaster without the relief funds. This might not be the case in reality. Moreover, the model does not incorporate the behaviour and perception of households to a larger extent. Therefore, the usefulness of intervention of relief funds in case of higher frequencies of hazard can only be explored using empirical studies.

Furthermore, ABM as a method was useful in incorporating the behaviour of residents and MFI to an extent. It was specifically useful in incorporating the formulation of groups by the poor, the diffusion through social networks and the preference given by MFI to either the well-off or the poor. Moreover, it also helped in efficiently simulating the influence of components of microcredits. With additional time, the model can be developed to a significant level of complexity that can help in the purposes of communication and learning. Apart from this, as the developed model is the first attempt to model an informal settlement in the context of microcredit and disasters, it paves the way for the development of more realistic and empirical models in this context. In this line, the following section provides the scope for future work.

7.2. Scope for Future Work

1. Validation of the model can be done with empirical data of an informal settlement in the global south.
2. More model parameters that enhance the behaviour and perception of residents, as well as MFIs, can be added to the model and used for a specific case study for pre-policy-implementation decision making.
3. The factor of the intensity of disaster can be added to the model to enhance the level. Along with this, with the help of an interview with experts in the field, the uncertainty in the characteristics of residents after receiving the loan can also be added to the model.
4. The model can also be enhanced with other microfinance services such as microinsurance and micro-savings. For example, the services can be coupled or immediately after a business is owned, the resident can be using these services.
5. Number of MFIs along with local money lenders and social networks can be added to the model with time to compare the microfinance service to social networks and local money lenders.

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APPENDIX – I: MODEL INTERFACE

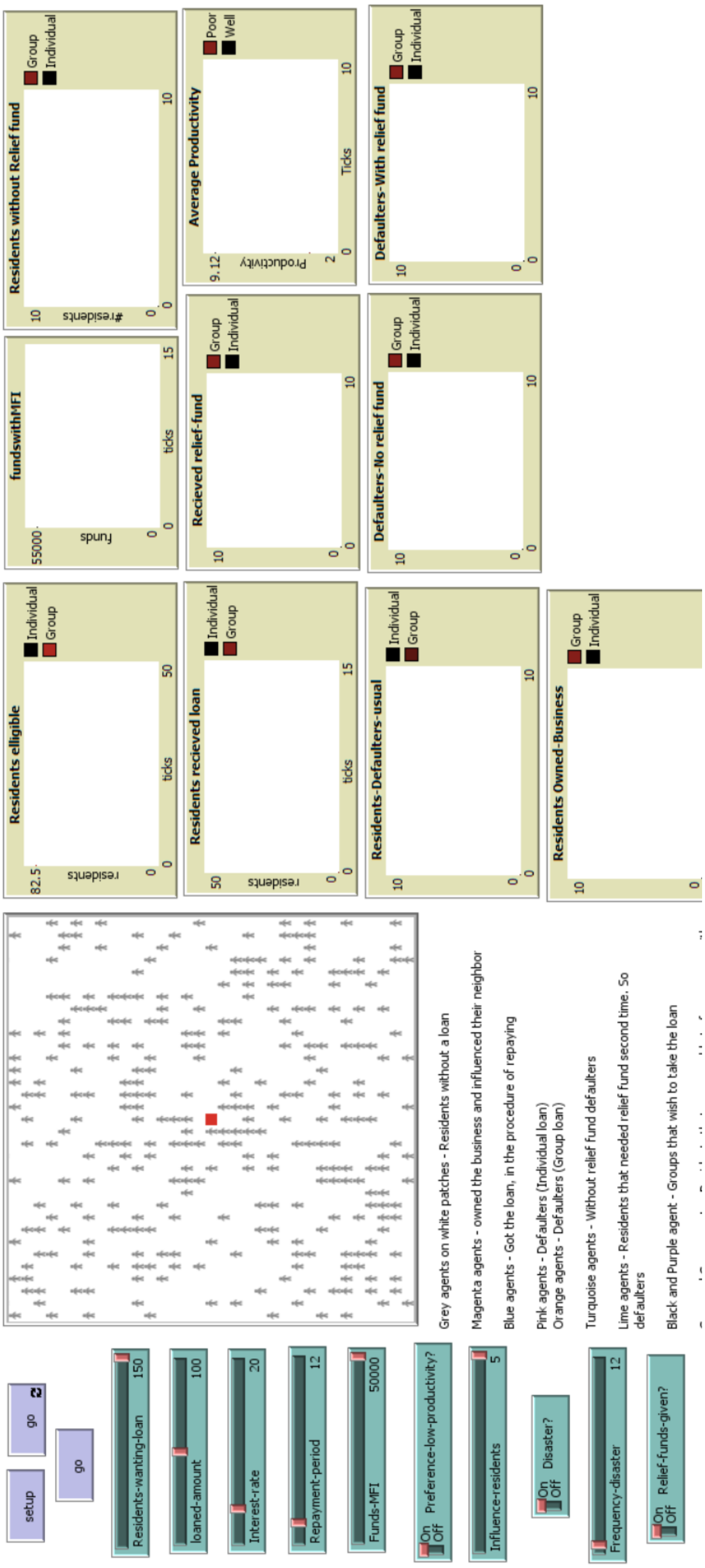

Figure 34 Interface of the model

APPENDIX – II: REGRESSION TABLES

Table 17 Regression Results - Number of residents owning business

	R Square	Adjusted R square
Model Summary	0.575	0.575
	0.449	0.449
ANOVA	**F ratio**	**Sig.**
F test	2317.085	0
	10854.557	0

Predictors	Unstandardized Coefficients		Standardized Coefficients	Sig.	Collinearity Statistics	
	B	**Std. Error**	**Beta**		**Tolerance**	**VIF**
(Constant)	225.435	3.626		0		
	118.057	1.665		0		
Initial Funds with MFI	0.0000	0.0000	0.038	0.000	1	1
	0.0000	0.0000	0.052	0.000	1	1
Amount of Loan	-1.313	0.014	-0.567	0	1	1
	43.359	0.486	0.191	0	1	1
Residents Wanting loan	0.091	0.013	0.041	0	1	1
	-1.229	0.006	-0.443	0	1	1
Repayment Period	14.363	0.199	0.43	0	1	1
	0.268	0.006	0.1	0	1	1
Preference for loan provision	5.14	1.126	0.027	0	1	1
	7.634	0.086	0.191	0	1	1
Residents getting Influenced	4.515	0.398	0.068	0	1	1
	4.904	0.486	0.022	0	1	1
Interest Rate	-1.042	0.025	-0.246	0	1	1
	5.433	0.172	0.068	0	1	1
Disaster-Frequency	-	-	-	-	-	-
	-0.853	0.011	-0.168	0	1	1
Provision of Relief funds	-	-	-	-	-	-
	2.44	0.014	0.365	0	1	1

Row 1 – Without disaster
Row 2 – With disaster --- In each predictor

Table 18 Regression Results - Defaulters

	R Square	Adjusted R square
Model Summary	0.482	0.482
	0.295	0.295
ANOVA	**F ratio**	**Sig.**
F test	1594.497	0
	5576.442	0

Predictors	Unstandardized Coefficients		Standardized Coefficients	Sig.	Collinearity Statistics	
	B	Std. Error	Beta		Tolerance	VIF
(Constant)	-4.79	1.877		0.011		
	41.85	1.019		0		
Initial Funds with MFI	0	0	0.101	0	1	1
	0	0	0.04	0	1	1
Amount of Loan	0.565	0.007	0.52	0	1	1
	0.479	0.004	0.319	0	1	1
Residents Wanting loan	0.063	0.007	0.06	0	1	1
	0.1	0.004	0.069	0	1	1
Repayment Period	-5.746	0.103	-0.367	0	1	1
	-2.373	0.053	-0.109	0	1	1
Preference for loan provision	1.943	0.583	0.022	0.001	1	1
	1.504	0.297	0.012	0	1	1
Residents getting Influenced	1.891	0.206	0.06	0	1	1
	4.048	0.105	0.093	0	1	1
Interest Rate	0.483	0.013	0.243	0	1	1
	0.33	0.007	0.12	0	1	1
Disaster-Frequency	-	-	-	-	-	-
	-1.28	0.009	-0.354	0	1	1
Provision of Relief funds	-	-	-	-	-	-
	-19.842	0.297	-0.162	0	1	1

Row 1 – Without disaster
Row 2 – With disaster --- In each predictor

Table 19 Regression Results - Time taken by residents

			R Square		**Adjusted R square**	
Model Summary			0.576		0.576	
			0.569		0.569	
ANOVA			**F ratio**		**Sig.**	
F test			12242.22		0	
			1909.845		0	
Predictors	**Unstandardized Coefficients**		**Standardized Coefficients**	**Sig.**	**Collinearity Statistics**	
	B	**Std. Error**	**Beta**		**Tolerance**	**VIF**
(Constant)	46.548	0.858		0		
	42.765	0.322		0		
Initial Funds with MFI	-7.52E-05	0	-0.063	0	0.998	1.002
	-7.28E-05	0	-0.062	0	0.996	1.004
Amount of Loan	0.06	0.004	0.112	0	0.933	1.071
	0.058	0.001	0.107	0	0.926	1.08
Residents Wanting loan	-0.238	0.003	-0.484	0	0.999	1.001
	-0.229	0.001	-0.467	0	0.997	1.003
Repayment Period	2.386	0.051	0.313	0	0.94	1.063
	2.762	0.018	0.365	0	0.929	1.076
Preference for loan provision	0.234	0.272	0.006	0.389	1	1
	0.134	0.094	0.003	0.155	1	1
Residents getting Influenced	-6.815	0.097	-0.459	0	0.997	1.003
	-6.332	0.034	-0.429	0	0.996	1.004
Interest Rate	0.004	0.006	0.004	0.53	0.981	1.019
	0.003	0.002	0.003	0.171	0.979	1.022
Disaster-Frequency	-0.114	0.003	-0.085	0	0.972	1.029
Provision of Relief funds	4.48	0.096	0.108	0	0.97	1.031

Row 1 – Without disaster
Row 2 – With disaster --- In each predictor

Table 20 Regression Results - Average Productivity

			R Square		Adjusted R square	
Model Summary			0.612		0.612	
			0.436		0.436	
ANOVA			**F ratio**		**Sig.**	
F test			2701.607		0	
			10326.877		0	
Predictors	**Unstandardized Coefficients**		**Standardized Coefficients**	**Sig.**	**Collinearity Statistics**	
	B	**Std. Error**	**Beta**		**Tolerance**	**VIF**
(Constant)	5.684	0.016		0		
	5.171	0.008		0		
Initial Funds with MFI	-1.72E-07	0	-0.007	0.222	1	1
	6.55E-07	0	0.021	0	1	1
Amount of Loan	-0.006	0	-0.591	0	1	1
	-0.006	0	-0.431	0	1	1
Residents Wanting loan	9.35E-05	0	0.009	0.107	1	1
	0.001	0	0.044	0	1	1
Repayment Period	0.067	0.001	0.439	0	1	1
	0.033	0	0.175	0	1	1
Preference for loan provision	0.011	0.005	0.012	0.03	1	1
	0.011	0.002	0.011	0	1	1
Residents getting Influenced	0.009	0.002	0.029	0	1	1
	0.005	0.001	0.012	0	1	1
Interest Rate	-0.005	0	-0.263	0	1	1
	-0.004	0	-0.164	0	1	1
Disaster-Frequency	0.012	0	0.39	0	1	1
Provision of Relief funds	0.211	0.002	0.195	0	1	1

Row 1 – Without disaster
Row 2 – With disaster --- In each predictor

Table 21 Regression Results - Average time taken to obtain the loan

	R Square	Adjusted R square
Model Summary	0.619	0.618
	0.656	0.655
ANOVA	**F ratio**	**Sig.**
F test	2485.634	0
	18512.641	0

Predictors	**Unstandardized Coefficients**		**Standardized Coefficients**	**Sig.**	**Collinearity Statistics**	
	B	**Std. Error**	**Beta**		**Tolerance**	**VIF**
(Constant)	21.542	0.359		0		
	17.189	0.1		0		
Initial Funds with MFI	-2.96E-05	0	-0.055	0	0.996	1.004
	-2.29E-05	0	-0.055	0	0.993	1.007
Amount of Loan	0.027	0.001	0.113	0	0.966	1.035
	0.024	0	0.125	0	0.936	1.068
Residents Wanting loan	-0.146	0.001	-0.652	0	0.998	1.002
	-0.121	0	-0.689	0	0.985	1.015
Repayment Period	0.81	0.021	0.236	0	0.971	1.03
	0.833	0.005	0.314	0	0.94	1.063
Preference for loan provision	0.183	0.113	0.01	0.105	0.999	1.001
	-0.134	0.029	-0.009	0	1	1
Residents getting Influenced	-2.321	0.04	-0.344	0	0.997	1.003
	-1.598	0.011	-0.298	0	0.985	1.015
Interest Rate	0.006	0.003	0.015	0.013	0.99	1.01
	0.005	0.001	0.016	0	0.985	1.016
Disaster-Frequency	-0.029	0.001	-0.065	0	0.979	1.022
Provision of Relief funds	0.986	0.029	0.067	0	0.983	1.018

Row 1 – Without disaster
Row 2 – With disaster --- In each predictor

Table 22 Regression Results - Average time taken to own the business

	R Square	Adjusted R square
Model Summary	0.738	0.738
	0.656	0.655
ANOVA	**F ratio**	**Sig.**
F test	4077.492	0
	18512.641	0

Predictors	Unstandardized Coefficients		Standardized Coefficients	Sig.	Collinearity Statistics	
	B	Std. Error	Beta		Tolerance	VIF
(Constant)	20.333	0.318		0		
	17.829	0.147		0		
Initial Funds with MFI	-3.13E-05	0	-0.055	0	0.998	1.002
	-1.52E-05	0	-0.025	0	0.996	1.004
Amount of Loan	-0.018	0.001	-0.071	0	0.933	1.071
	-0.024	0.001	-0.089	0	0.926	1.08
Residents Wanting loan	-0.131	0.001	-0.56	0	0.999	1.001
	-0.125	0.001	-0.501	0	0.997	1.003
Repayment Period	2.081	0.019	0.574	0	0.94	1.063
	2.229	0.008	0.578	0	0.929	1.076
Preference for loan provision	-0.167	0.101	-0.008	0.097	1	1
	-0.13	0.043	-0.006	0.002	1	1
Residents getting Influenced	-2.22	0.036	-0.314	0	0.997	1.003
	-2.016	0.015	-0.268	0	0.996	1.004
Interest Rate	-0.034	0.002	-0.076	0	0.981	1.019
	-0.025	0.001	-0.052	0	0.979	1.022
Disaster-Frequency	-0.052	0.001	-0.076	0	0.972	1.029
Provision of Relief funds	2.672	0.044	0.126	0	0.97	1.031

Row 1 – Without disaster
Row 2 – With disaster --- In each predictor

Table 23 Regression Results – Funds with MFI by the end of the simulation

	R Square	Adjusted R square
Model Summary	0.916	0.916
	0.904	0.904
ANOVA	**F ratio**	**Sig.**
F test	15749.197	0
	84714.132	0

Predictors	Unstandardized Coefficients		Standardized Coefficients	Sig.	Collinearity Statistics	
	B	**Std. Error**	**Beta**		**Tolerance**	**VIF**
(Constant)	-8263.725	332.727		0		
	-8578.539	138.587		0		
Initial Funds with MFI	0.978	0.003	0.938	0	0.998	1.002
	0.978	0.001	0.922	0	0.996	1.004
Amount of Loan	5.116	1.411	0.011	0	0.933	1.071
	10.479	0.552	0.021	0	0.926	1.08
Residents Wanting loan	1.234	1.243	0.003	0.321	0.999	1.001
	-1.332	0.483	-0.003	0.006	0.997	1.003
Repayment Period	837.362	19.902	0.125	0	0.94	1.063
	976	7.72	0.143	0	0.929	1.076
Preference for loan provision	-243.618	105.477	-0.007	0.021	1	1
	-247.118	40.586	-0.007	0	1	1
Residents getting Influenced	-165.3	37.638	-0.013	0	0.997	1.003
	-171.548	14.556	-0.013	0	0.996	1.004
Interest Rate	116.878	2.389	0.142	0	0.981	1.019
	131.083	0.922	0.156	0	0.979	1.022
Disaster-Frequency	-56.407	1.336	-0.047	0	0.972	1.029
Provision of Relief funds	1218.353	41.533	0.032	0	0.97	1.031

Row 1 – Without disaster
Row 2 – With disaster --- In each predictor

APPENDIX – II: MODEL CODE

```
globals [ counter
  current
  repay-amount
  time-stop
  step
]

residents-own [ start-patch
  productivity
  want
  repay-freq
  asked-for-loan
  got-loan
  leader
  grp-prod
  income
  repay-ability1
  combined-income
  relief-fund?
  time-taken
  relief-times
  repayment-period1
  relief-month
  time-taken-loan
  status
 group-members
 savings
]

patches-own [ funds ]

links-own [ PL ]

breed [residents resident ]

to setup
  ca
  random-seed 11
  set counter 0
  set current 0
  set step 0
  setup-patches
 ; setup-residents
  reset-ticks
end
```

```
to setup-patches
  ask patches [ ifelse (pxcor = 0) and (pycor = 0)
    [set pcolor red  set funds funds-MFI ]
    [set pcolor white ]]
  ask n-of 300 patches with [pcolor = white] [sprout-residents 1
  [set productivity random 10 + 1
  set shape "person"
  set color grey
  ;set pcolor scale-color green productivity 8 1
 set start-patch patch-here
  ;set want random 2
  set repay-freq 0
      set asked-for-loan "no"
  set leader self
  set grp-prod productivity
  set income 0
  set repay-ability1 0
  set relief-fund? "no"
  set repayment-period1 repayment-period
  set relief-month 0
      if productivity >= 7 [ set status "well" ]
      if productivity < 7  [set status "poor"]
  ]  ]

  ask  n-of  (residents-wanting-loan  /  2)  residents  with  [status  =
"poor"] [set want 1]
  ask  n-of  (residents-wanting-loan  /  2)  residents  with  [status  =
"well"] [set want 1]

end

to go

ifelse count residents with [ color = blue and pcolor = white ] = 0
and [funds] of patch 0 0 < 2 * loaned-amount  [ stop ]

[ifelse all? residents [color != blue] and all? residents [color !=
green] and count residents with [ color = grey and productivity >= 7
and want = 1 ] = 0 and
    count residents with [color = grey and productivity < 7 and count
link-neighbors = 0 and want = 1] < 2 [ stop]
    [if all? residents [color != blue] and count residents with [color
= grey and productivity >= 7 and want = 0] + count residents with
[color = grey and productivity < 7 and count link-neighbors = 0 ] +
      count residents with [color = magenta] + count residents with
[color = green] + count residents with [ color = grey and count link-
neighbors > 0 ]
```

```
    + count residents with [color = cyan and count link-neighbors > 0
] + count residents with [color = lime] + count residents with [color
= turquoise] + count residents with [ color = pink]
      + count residents with [color = orange] + count residents with
[color = sky] = 300 [ stop] ]
  ]

if ticks = 120  [stop]

 ifelse disaster?
     [ if (ticks mod frequency-disaster = 0) and (ticks != 0) ;
        [
          ifelse Relief-funds-given?
          [

          ask-relief

             ask residents with [ pcolor = red and color = blue and
relief-fund? = "no" ]
          [
            move-to start-patch set color turquoise set productivity
productivity - 1
          ask link-neighbors [ set color turquoise set productivity
productivity - 1 ] ;
          ]
        ]
          [ask-relief1]
        ]
         ]
    [  ]

  ask-loan

 if any? residents with [(color = blue) and count link-neighbors = 0
and repay-freq < repayment-period1 and patch-here = start-patch]
    [repay-loan3]

 if any? residents with [(color = blue) and count link-neighbors = 0
and repay-freq = repayment-period1]
    [
     ask residents with [(color = blue) and count link-neighbors = 0
and repay-freq = repayment-period1]
      [
      set productivity productivity + 1
      set color green
      set time-taken ticks ; time-taken to own the business
      ]
    ]
```

```
 if any? residents with [(color = blue) and count link-neighbors > 0
and (leader = self) and repay-freq < repayment-period1 and patch-here
= start-patch]
    [repay-loan4]

  if any? residents with [(color = blue) and count link-neighbors > 0
and repay-freq = repayment-period1]
    [
     ask residents with [(color = blue) and count link-neighbors > 0
and repay-freq = repayment-period1]
      [
      set productivity productivity + 1
      ask link-neighbors [ set productivity productivity + 1 ]
      set color green
      ask link-neighbors [ set color green ]
      set time-taken ticks
      ask link-neighbors [ set time-taken ticks ]
      ]
   ]

  while [ (count residents with [color = grey and want = 0 and asked-
for-loan = "no" and count link-neighbors = 0] >= influence-residents)
and (count residents with [ (color = green) ] > 0) ]
    [influence]

tick

end

to ask-loan
  if any? residents with [ (productivity >= 7) and (color = grey) and
(want = 1) and (asked-for-loan = "no")]
    [ ask residents with [(productivity >= 7) and (color = grey) and
(want = 1) and (asked-for-loan = "no") ]  [move-to patch 0 0 ] ]

  if any? residents with [ (productivity < 7) and (color = grey) and
(want = 1) and (asked-for-loan = "no") and ( count link-neighbors =
0) ]
   [ Form-group]
  let group-leaders residents with [ (color = violet) and (want = 1)
and (asked-for-loan = "no") and (leader = self) ]
  ask group-leaders [ move-to patch 0 0 ]

  ask patch 0 0 [
      let all-asking residents-on patch 0 0

     while [(funds >= 2 * loaned-amount) and (count all-asking != 0 )]
```

```
[ ifelse preference-low-productivity?
  [
    ask min-one-of all-asking [productivity]
    [
    set color blue
    ifelse productivity >= 7
      [  ask patch-here [ set funds funds - loaned-amount ] ]
    [ ask patch-here [ set funds funds - 2 * loaned-amount ]]
    move-to start-patch
    set want 0
    set asked-for-loan "yes"
    set income (40 + productivity * 2 )
    set time-taken-loan ticks

      ask link-neighbors
      [
     set income 40 + productivity * 2
     set color yellow
     set asked-for-loan "yes"
     set want 0
     set time-taken-loan ticks
     ]
    ]

   set all-asking residents-on patch 0 0
 ]

 [  ask max-one-of all-asking [productivity]
   [
     set color blue
    ifelse productivity >= 7
      [  ask patch-here [ set funds funds - loaned-amount ] ]
    [ ask patch-here [ set funds funds - 2 * loaned-amount ]]
    move-to start-patch
    set want 0
    set asked-for-loan "yes"
    set income (40 + productivity * 2 )
    set time-taken-loan ticks

    ask link-neighbors
      [
     set income 40 + productivity * 2
     set color yellow
     set asked-for-loan "yes"
     set want 0
     set time-taken-loan ticks
     ]
    ]
```

```
       set all-asking residents-on patch 0 0
     ]
     ]
   ]
    ask residents with [ color = blue and count link-neighbors > 0 ] [
     set repay-ability1 repay-amount-group / (count link-neighbors +
1)
     set combined-income sum [income] of residents with [leader =
myself]

     ask link-neighbors [ set combined-income [combined-income] of
myself]
     ]

end

to repay-loan3

  let residents1 residents with [(color = blue) and (repay-freq <
repayment-period1 ) and count link-neighbors = 0 and patch-here =
start-patch ]

     ask residents1
       [ ifelse repay-amount-individual <= (1 * income / 3)
        [
        move-to patch 0 0
        Let individual-loaned-residents residents1 with [pcolor = red
]


           ask patch 0 0 [ set funds funds + repay-amount-individual
* count individual-loaned-residents ]

           ask individual-loaned-residents [  move-to start-patch set
repay-freq repay-freq + 1 ]
          set savings (income / 3) - repay-amount-individual
       ]
       [set color pink
       set productivity productivity - 1
        set savings (combined-income / 3) - repay-amount-individual
        ]
  ]
end

to repay-loan4
```

```
   let residents1 residents with [(color = blue) and (repay-freq < repayment-period1 ) and count link-neighbors > 0 and patch-here = start-patch] ;  (repay-amount-group / count link-neighbors) <= (3 * income / 4)

    ask residents1
      [ ifelse  (1 * combined-income / 3) >= repay-amount-group
        [
        move-to patch 0 0
        Let group-loaned-residents residents1 with [pcolor = red and count link-neighbors > 0]

           ask patch 0 0 [
               set funds funds + repay-amount-group * count group-loaned-residents
                ]

           ask group-loaned-residents [
              move-to start-patch
              set repay-freq repay-freq + 1
               ]
        set savings (combined-income / 3) - repay-amount-group
      ]
        [ set color orange
        ask link-neighbors [ set color orange
          set productivity productivity - 1
          set savings (combined-income / 3) - repay-amount-group
        ]
        set productivity productivity - 1
        set savings (combined-income / 3) - repay-amount-group
      ]

  ]

end

to influence

  ask one-of residents with [ (color = green)  ]

   [ Let resident-new  min-n-of influence-residents ( residents with [ (color = grey) and (want = 0) and (asked-for-loan = "no") and count link-neighbors = 0 ] ) [distance myself]


    if count resident-new >= influence-residents

    [ ask resident-new [ set want 1  ]  ]
```

```
       set color Magenta
    ]

end

to-report repay-amount-individual
  report loaned-amount * ((interest-rate / 100) + 1) / repayment-
period
end

to-report repay-amount-group
  report 2 * loaned-amount * ((interest-rate / 100) + 1) / repayment-
period
end


to ask-relief


  ask residents with [color = blue ] ; agentset that can ask for relief
(green is because if the resident is influencing one person it stops
influencing in the procedure influence)
      [ ifelse relief-times = 0 [move-to patch 0 0] [set color lime
set productivity productivity - 1 ask link-neighbors [set color lime
set productivity productivity - 1]]]

   ask patch 0 0 [
      let affected-residents residents with [ color = blue and relief-
times = 0]
      let residents2 affected-residents with [ pcolor = red ]   ; the
agentset that can ask for relief on the MFI patch

    while [ (funds >= 2 * loaned-amount ) and (count residents2 != 0)
]  ; As an example relief amount is taken as half the amount

        [ ifelse preference-low-productivity?
          [
          ask min-one-of residents2 [productivity] [ move-to start-
patch set relief-fund? "yes" set relief-times 1
          set relief-month ticks
          set repayment-period1 repayment-period + repayment-period /
2
          ask link-neighbors [ set relief-fund? "yes" set relief-times
1
          set relief-month ticks
          set repayment-period1 repayment-period + repayment-period /
2
```

```
          ] ]
         set funds funds - (loaned-amount / 2)
         set residents2 affected-residents with [ pcolor = red ]
          ]
          [
          ask max-one-of residents2 [productivity] [ move-to start-
patch set relief-fund? "yes" set relief-times 1
          set repayment-period1 repayment-period + repayment-period /
2
          ask link-neighbors [ set relief-fund? "yes"  set relief-
times 1
          set relief-month ticks
          set repayment-period1 repayment-period + repayment-period /
2
         ] ]
         set funds funds - (loaned-amount / 2)
         set residents2 affected-residents with [ pcolor = red ]
          ]
    ]
  ]
end

to ask-relief1
  ask residents with [color = blue]
      [ set color sky set productivity productivity - 1
        ask link-neighbors [ set color sky set productivity
productivity - 1]
          ]
end

to get-relief
     ask patch 0 0 [
      let affected-residents residents with [ color = blue ]
      let residents2 affected-residents with [ pcolor = red ]   ; the
agentset that can ask for relief on the MFI patch

    while [ (funds >= loaned-amount / 2) and (count residents2 != 0)
]  ; As an example relief amount is taken as half the amount

        [ ifelse preference-low-productivity?
          [
          ask min-one-of residents2 [productivity] [ move-to start-
patch set relief-fund? "yes" set relief-times counter + 1
          set repayment-period1 repayment-period + repayment-period /
2 * relief-times
          ask link-neighbors [ set relief-fund? "yes" set relief-times
counter + 1
```

```
          set repayment-period1 repayment-period + repayment-period /
2 * relief-times
          ] ]
         set funds funds - (loaned-amount / 2)
         set residents2 affected-residents with [ pcolor = red ]
          ]

          [
          ask max-one-of residents2 [productivity] [ move-to start-
patch set color blue set relief-fund? "yes" set relief-times counter
+ 1
          set repayment-period1 repayment-period + repayment-period /
2 * relief-times
          ask link-neighbors [ set relief-fund? "yes"  set relief-
times counter + 1
          set repayment-period1 repayment-period + repayment-period /
2 * relief-times
         ] ]
         set funds funds - (loaned-amount / 2)
         set residents2 affected-residents with [ pcolor = red ]
          ]
     ]
   set counter counter + 1
  ]
end

to form-group
    Let singles residents with [ (color = grey) and (productivity <
7) and  (want = 1) and (asked-for-loan = "no")  and (grp-prod < 8) and
(count link-neighbors = 0 )]  ; these are the agents

    while [count singles > 1 ]

     let  nearest-neighbors  min-one-of  (other  singles)  [distance
myself]  ; to link with the nearest resident


    if nearest-neighbors != nobody ; if nearest neigbor is not nobody

        [ create-link-with nearest-neighbors
          ask link-neighbors [set leader [leader] of myself ]  ; so
that there is one leader of each group
         set  grp-prod  productivity  +  [productivity]  of  nearest-
neighbors
         ask link-neighbors [set grp-prod [grp-prod] of myself]

      show (sentence "prod 1 " productivity)
      show (sentence " prod 2"  [productivity] of nearest-neighbors)
```

```
        show grp-prod

      if grp-prod! =   (productivity + [productivity] of nearest-
neighbors ) [show " grp-prod wrong" ]

    ]
    set singles residents with [ (productivity < 7) and (color = grey)
and (want = 1) and (asked-for-loan = "no")  and (grp-prod < 8) and
(count link-neighbors = 0)]

         ifelse grp-prod >= 8
    [ set color violet
      ask link-neighbors [set color black]
    set group-members 1 + count link-neighbors
      ask link-neighbors [set group-members 1 + count link-neighbors]
]

    [ set color cyan
      ask link-neighbors [set color cyan]
      if count residents with [ (productivity < 7) and (color = grey)
and (want = 1) and (asked-for-loan = "no")  and (grp-prod < 8) and
(count link-neighbors = 0)] != 0
       [ form-group-2
       set singles residents with [ (productivity < 7) and (color =
grey) and (want = 1) and (asked-for-loan = "no")  and (grp-prod < 8)
and (count link-neighbors = 0)] ]
  ] ] ]
end

to form-group-2
    Let nearest-neighbor min-one-of (residents with [ (productivity <
7) and (color = grey) and (want = 1) and (asked-for-loan = "no")  and
(grp-prod < 8) and (count link-neighbors = 0)]) [distance myself]
   if nearest-neighbor != nobody
    [
     create-link-with nearest-neighbor
      ask link-neighbors [ set leader [leader] of myself ]
      set grp-prod grp-prod + [productivity] of nearest-neighbor
      ask link-neighbors [set grp-prod [grp-prod] of myself]

      ifelse grp-prod >= 8 [ set color violet
        ask link-neighbors [set color black]
   set group-members 1 + count link-neighbors
    ask link-neighbors [set group-members 1 + count link-neighbors] ]
[form-group-2]
  ]

end
```