Rural Microfinance and Climate Change: Geographical Credits Allocation and Vulnerability. An Analysis of Agroamigo in Brazil’s Northeastern States

Davide Forcella, Rafael Moser and Lauro Emilio Gonzales Farias

In this paper we discuss the climate change (CC) vulnerability for rural microfinance. In particular, we seek to assess how the geographical allocation of services influences the vulnerability of microfinance institutions and clients to climate change impacts. As case study we analyse the biggest rural microfinance programme in Brazil: AgroAmigo, that operates in a particularly drought vulnerable area, i.e. the Northeastern region. Accordingly, we implement a correlation analysis between Agroamigo’s geographical credit allocation and local climate change vulnerabilities. The paper shows that the geographical distribution of services increases the climate change vulnerability of the microfinance institution’s (MFI) portfolio, whilst not necessarily offsetting CC vulnerability of clients because fewer credit amounts per person is allocated to the most vulnerable regions. Such results call for a better understanding of the climate change risk and the introduction of tailored strategies for microfinance programmes that could, at once, provide more adapted services to the most vulnerable population while aid manage and/or mitigate potential climatic risks of MFI’s portfolio, in particular those operating in hazard prone areas.

Keywords: Climate Change Adaptation, Climate Change Vulnerability, Geographical Credits Allocation, Agricultural Microfinance, Rural Microfinance, Green Microfinance, Climatic Risk, Credit Risk, Brazil, Agroamigo

JEL Classifications: O13, Q14, Q54, G21

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INTRODUCTION

There are increasing scientific evidences that the Earth’s Climate is changing and that the main driver of this change are the human activities (IPCC, 2014a). Mean surface air temperature is likely to increase more than 1.5°C by the end of the century (compared to the reference period 1850-1900) in the majority of future scenarios, with the probability to exceed 4°C for certain scenarios. Effects are forecasted also at the short and medium terms with temperature increases varying between 0.3°C and 0.7°C for the period 2016-2035 and 0.3°C to 4.8°C in the period 2081-2100 relative to 1986-2005. The majority of Climate Change (CC) consequences are likely to persist for various centuries under all scenarios (IPCC 2014a). Moreover, higher average temperature implies more energy in the atmosphere and the oceans that could contribute to increase frequency and intensity of extreme events such as heat waves and/or heavy precipitations.

CC is a complex multidimensional phenomenon, interacting with local and global socio-economic dynamics. Natural and human systems are vulnerable to CC effects, and due to the intensity and rapidity of climate evolution, are not likely to adapt, on a sounder pace, to such new and evolving climatic conditions. Vulnerability to CC is the result of the interaction between weather hazards (the external factor) and the specific degrees of resiliency (ability to adapt) of ecosystems and humans (the internal factor) (IPCC, 2014b). Different geographical locations are exposed to different climate trends and different level of degrees of weather hazards, and inequalities in temperature and precipitations among various regions and seasons are likely to increase (IPCC, 2014a).

Non-climatic issues and multidimensional inequalities, as a result of uneven development processes, support uneven levels of population’s resilience and vulnerability to CC. Geographical areas, poverty, local institutions’ governance and performance, reliance on natural resources, assets, human capital, access to insurances, formal financial tools, etc., are determinant factors influencing the degree of vulnerability of people and organisations at large. Poor people in developing countries, especially the ones involved in agricultural activities, and the institutions interacting with them, are the most exposed to CC (IPCC, 2014b). They will indeed bear the heaviest burden even if they contributed the least to CC.

A great deal of poor households in developing countries directly or indirectly use microfinance (MF) products to support their consumption needs and livelihoods (Morduch, 1999; Hassan, 2010). MF clients, at the bottom of the wealth pyramid and with limited adaptive mechanisms in
hand, and microfinance institutions (MFIs) interacting with them, are then increasingly vulnerable and exposed to CC impacts as conditions worsen (Hammill et. al. 2008; Rippey, 2012, Dowla, 2009). This is even truer for those clients that find in agriculture their main source of income and employment, as well those MFIs financing such activities. Due to poverty, low human-physical and financial capital, reliance on natural ecosystems and regular seasonal cycle, and too often linked to buyers-driven value chains, the poor rural households will be severely affected. MFIs providing services to this group, on the other hand, don’t seem to have clear formalised mechanisms or policies to cope with such CC related vulnerabilities.

However, CC will likely affect MFIs both directly and indirectly (Hammill et. al. 2008; Rippey, 2012, Dowla, 2009). The direct risk comes from the exposure of physical MFIs’ infrastructures and staff members to CC hazards, while the indirect risk is due to clients’ vulnerability. With extreme weather events on the rise and modified weather patterns and seasons, default tides, widespread claims on savings and on insurance policies, as well availability of cash in the very short run to help clients cope with daily necessity and sustain their economic activities are very much likely to increase. For many years, CC actions seemed an intangible luxury for MF providers. Today, however, "climate proofing" MF appears to be essential for the future of the industry, in particular for those MFIs operating in rural areas (Mckee, 2008, p. 37).

In this paper, we would like to do dig a bit further into the interaction between rural MF activities and the CC related risks for MFIs and clients. In particular, we seek to investigate how the underlying drivers that lead a rural MF programme to establish and expand its activities and credit disbursement in certain areas, as opposed to others, influence the CC related vulnerability of an MFI and its clients. Our research question is then:

- How does geographical credit allocation influence CC vulnerability of clients and MFIs?

To answer this question, we investigate the case of AgroAmigo, Brazil’s largest rural microfinance programme. Agroamigo offers a compelling case study since it operates in an area which is at once highly exposed to weather events and CC, in particular drought, and home to Brazil’s poorest population, especially the rural poor.

To the best of our knowledge, this paper is the first study of this kind, and it is aimed to i) foster reflection on possible CC vulnerabilities of MFIs and their clients; ii) inspire CC risk
management practices; and iii) hopefully, provide insights on possible products and strategies that could both protect, or at least mitigate, an MFI’s portfolio from CC related risks and enhance the adaptive capacity of clients.

From our analysis it emerges that Agroamigo, due to direct choice or to a multiplicity of related or unrelated reasons, allocated its services according to markets demand and socio-economic opportunities. These strategies indirectly increase its marginal exposure to CC while at the same time not offsetting CC vulnerability of the population with least resilience capacities. It follows that total rural population and total rural GDP are factors that increase the credit allocations in a given geographical region. However, poorer states, measured in terms of agricultural output per person, received the least amount of credits per person. Using various CC vulnerability indices we observe moreover that the Programme provided more credits, in terms of total volume and total number of credits, to states that are more vulnerable to CC, potentially increasing vulnerability of its portfolio. At the same time, Agroamigo also provided fewer credits per person and smaller loan size per person in states with higher vulnerability to CC, leaving more exposed the population potentially more vulnerable to CC.

Such results call for a better understanding of potential CC risks and the introduction of tailored strategies for rural microfinance programmes that could, all at once, provide more adapted services to those greater exposed and vulnerable to CC, while managing climatic risks of MFIs’ portfolios.

The rest of the paper is organised as follows: in section 1 we provide some literature review on the linkage between MF and CC vulnerability and adaptation, before addressing some of the results of previous studies analysing the drivers that influence MF services distribution and in particular the geographical credits allocation. In section 2, we illustrate our methodology, whereas in section 3, we provide a brief introduction to Agroamigo. Section 4, builds on our data analysis and our main results, whilst last section provides some conclusions and perspectives on the topic.

1. LITERATURE REVIEW

Previous studies have shown evidences that CC may *de facto* affect an MFI’s operations and its clients’ activities. In Castellani and Cincinelli (2014) the portfolios of a set of MFIs operating in Africa were analysed against drought events, and it emerged that droughts have significant
influence on the MFIs’ credit and liquidity risks. Analysing a group of 22 MFIs, Agrawala and Maelis (2010) discuss potential relations between CC vulnerability and MFIs’ operations in Nepal and Bangladesh, as well potential opportunities and trade-offs stemming from the combination of MF and CC adaptation. In a previous paper (Moser, Forcella, Gonzalez, 2015), we have performed a comparative analysis of CC vulnerability and opportunities for the two largest rural MF programmes in Brazil and their clients, and we have underlined the additional credit risks due to CC, as well the opportunities to develop CC adapted strategies. From an empirical viewpoint, some few specific MF programmes have been designed to support CC adaptation (see, for instance, Forcella, 2013a; Forcella 2013b; EcoMicro, 2014; MEbA, 2012).

MF has been argued to potentially be a powerful tool to contribute to foster CC adaptation (Hammill et. al. 2008; Rippey, 2012, Dowla, 2009) mainly due to its clients proximity and products. However, even if MF is often presented as a means to bolster financial inclusion and, in particular, poverty alleviation, its development tended to be uneven, and, pushed by a commercialisation strategy, ending up privileging the better off among the poor (Navajas et al., 2000). The majority of investments in the MF industry is concentrated in a limited number of bigger organisations, and the recent transformation of various NGOs in commercial banks has generated a sense of “mission drift” by some actors. It is then important to analyse how the development of MF interacts with the macro-environment and institutions. In Ahlin and Maio (2011), Cull et al (2013), and Vanroose and D’Espallier (2013) it was indeed found that the local economy and financial sector do influence the presence, penetration and performance of MF. Vanroose (2014) is one of the first studies about the influence that the socio-economic and financial characteristics of a region exert on the geographical distribution of MFIs. The analysis, conducted in Peru, suggests that MFIs tend to expand in districts with higher socio-economic development levels and that the presence of financial intermediaries tends to increase the probability that another MFI will eventually open a branch in the same region. Her results point towards a commercial rationale for the expansion of MF services in a given geographical area, with the risk of reinforcing uneven development and regional socio-economic inequalities (Bebbington, 2004; Fouillet, 2009).

The economic rationality in the credit distribution strategies underlined by these papers, introduce an important factor that should be carefully considered when discussing vulnerability and adaptation to CC for MFIs. Indeed, in the case of CC and agricultural MF, it would be very interesting to better understand whether and how the geographical distribution of branches and activities of MFIs interact with poverty levels, agriculture development and vulnerability to CC, as
well as how the consequent geographical distribution of services influence CC vulnerabilities of MFIs’ portfolio and clients.

2. METHODOLOGY

Stimulated by the uneven effect of CC, the socio-economic inequalities that sustain CC vulnerability and the recent market rationale behind the provision of MF services, in this paper we seek to better understand the geographical correlation between MF activities and potential CC vulnerabilities of the population they provide services to, as well the level of exposure of the loan portfolio to weather related impacts.

As case study for such interaction we analyse the geographical distribution of the financial operations of the largest rural microfinance programme in Brazil: namely Agroamigo, over Brazil’s nine North-Eastern (NE) states where it operates. The nine states have different levels of economic development, health assistance, and probability of CC hazards, being predominant intense drought events. These differences influence the overall vulnerability of the population to CC related impacts.

To assess how the geographical allocation of credits relates, positively or negatively, to CC vulnerability, we cross Agroamigo portfolio data with the projected CC vulnerability for each estate in which Agroamigo operates. More specifically, we built on IPCC (2007), Brazilian Spatial Research Centre (INPE) data, and Barbieri et. al (2008) to measure the vulnerability of Brazil’s Northeastern States to CC under A2 and B2 scenarios, as established by IPCC (2007) – high and low emission scenarios, respectively. Barbieri et. al (2008) developed four sub-indexes taking into account various CC vulnerability dimensions. They computed the indices for every state in the North-East. The four indices, computed according to B2 and A2 scenarios, are:

- Health Vulnerability Index (HVI): it considers the spread of diseases and children mortality;
- Desertification Vulnerability Index (DVI): it considers the absolute and relative amount of area at risk of desertification;
- Economic and Demographic Vulnerability Index (EDVI): it considers the effects of weather pattern on the region’s GDP, employment rate and migration fluxes;
- Cost Vulnerability Index (CVI): it considers the health expenses related to change in weather conditions.
A General Vulnerability Index (GVIav) is constructed as the simple average of the above four sub-indices and it provides for a global, holistic view on the population’s vulnerabilities to climate change in every NE state. Every index runs from 1 (high vulnerability) to 0 (low vulnerability).

Applying the indexes to a microfinance viewpoint, we believe that the geographical allocation and services distribution of MF in a CC prone area may increase or decrease its overall climatic risk and, at the same time, influence potential climatic risks for clients. For example, if an MFI disburses more credits in regions that are or will likely be more affected by CC, other things being equal, it will reasonably decrease the vulnerability of the population to whom it provides services to, but at the same time, without any specific adaptation strategy, it would increase the CC risk exposure of its loan portfolio. Vice-versa, if an MFI would instead reduce its services provision in areas that are or will likely be more affected by CC, it will reduce its CC portfolio risk, ceteris paribus, but however, it also would marginally reduce the adaptation capacity of clients as credit access declines.

We have then made the simplifying operational assumptions that:

• the access to formal finance reduces CC vulnerability of poor population due to the possibility to use financial tools to foster incoming generating activities, to cope with weather shocks, or to use borrowed money to finance other pressing needs. Hence, scaling up the provision of financial services in a geographical area allegedly vulnerable and exposed to CC should somehow decrease CC related vulnerability of clients;

• unlike that, the more an MFI’s portfolio is concentrated in vulnerable areas [coupled with the absence of specific actions to reduce vulnerability], the higher its exposure to risks stemming from CC.

To try to disentangle the MF and the clients’ vulnerability to CC, we introduce two proxies, in our analysis:

• the cumulated volume and number of credit from 2005 until June 2013\(^1\) per state are used as proxies for MFI’s vulnerability. The rationale is that the bigger is the amount of the portfolio concentrated in more vulnerable states, the greater the climatic risk to the MFI’s portfolio, while, *vice-versa*, the smaller the portfolio concentrated in more vulnerable states, the lower the CC vulnerability of the MFI’s portfolio.

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\(^1\) This specific choice of dates is due to data availability and because the programme started in 2005.
• the cumulated volume and number of credits per person employed in rural activities from 2005 until June 2013\textsuperscript{2} are used as proxies for population vulnerability in the various states. The rationale is that, everything else being equal, a person with more credits or greater loan size is less vulnerable to CC, thanks to the additional coping tool provided by formal MF.

We then calculate the Pearson and Spearman correlations between socio-economic indicators associated with CC vulnerability [and, in particular, the four vulnerability indices], and the cumulated total and per capita volume, as well as number of credits in the various states. The use of two correlations Pearson and Spearman aims to strengthen the results of our analysis. In fact, the Pearson correlation measures how well the dependency of two statistical variables can be approximated by a linear function, while the Spearman correlation is a non-parametric measure of correlation and is employed to assess how two statistical variables can be described by a monotonic function. The values for both correlations measurement run from -1 – perfect negative correlation: when one variable increase the other one decrease, to 1 – perfect positive correlation: when one variable increases the other one increases too, and vice-versa, with 0 the value corresponding to no dependency between the two variables.

Before starting our analysis it is worth stating what the main limitations of our analysis are, and how we take them into account in our investigations:

i. \textit{Data availability}: we would have wished to collect data for each branch and client, as well as for each activity financed by Agroamigo and local poverty levels. However, we did not have access to such database and thus we had to limit our analysis to aggregate data per state. We believe that such data are enough, as a first attempt, to explore this incipient arena, also due to the inability to forecast CC effects on small geographical areas and at household level. To partially offset such limitation, we use various socio-economic indicators to strengthen our analysis. We hope to have access to better data in the near future;

ii. \textit{Correlation between current and past credit provision and the medium-to-long term CC vulnerabilities}: our analysis correlates what happened until now (present) with what will

\textsuperscript{2} This specific choice of dates is due to data availability and because the programme started in 2005.
probably occur in the future. This may seem quite unsatisfactory, however, it appears as an intrinsic problem related to CC vulnerability analysis. By definition, CC refers to a long term risk, while predicking the evolution of an MFI’s portfolio in the long term is somewhat cumbersome. By implementing such analyses, we are somehow intrinsically making the simplifying assumption of a “business as usual” (BAU) evolution of an MFI’s product envelope and loan portfolio. In other words, trends observed so far in MF services distribution is a faithful picture of what will perhaps happen in the future. Moreover, the past and current credit allocation provides for a hint on future drivers of an MFI’s outreach and its impact on population resilience and MF portfolio. In addition, the historical credit allocation could be useful to assess if an MFI has specific strategies to cope with CC. Resilience building is a long term process and an early start can provide comparative advantages. As additional comment it could be argued that CC will essentially worsen the present climatic trends concerning temperature increase, drop in rainfalls and more frequent extreme weather events. Hence, comparing how the present credit distribution responds to current weather related vulnerabilities may offer an appealing proxy for future vulnerability forecasts. In conclusion, even if we correlate different times, this analysis should provide answers to the questions: what has Agroamigo done until now with respect to the future CC risk? Is Agroamigo looking to mitigate now future CC related risks and build resilience? Are current Agroamigo’s actions going to increase or decrease its marginal vulnerability to CC? To improve this situation we would have liked to use the recorded effect of past climatic trends and extreme events [that could be comparable with CC forecasted events in similar locations] on the local population and MFI portfolio to infer the future vulnerability to CC. However, the operations of Agroamigo are bit too recent to have enough historical data and moreover we did not have access to disaggregated data.

iii. Government driven MF: The use of Brazil as a first case study for our research objectives could be criticised due to the peculiarity of MF in Brazil (mainly public driven) with respect to the reality of MFIs in other countries. We accept this critique. However, we believe that the public character of MF in Brazil could reinforce some aspects of the present analysis, while weaken others. For instance, it would be expected that a public entity is less influenced by market logics, that it fosters more proactive actions, and that it is pushed by social logic and societal objectives. Accordingly, we could argue that the loan portfolio of a
public financed MFI should tend to be more exposed to CC as it absorbs covariant risks imbued in credit provision in hazard prone areas and in key weather sensitive activities, e.g. livestock. At the same time, public-led MFIs should be more attuned to clients’ vulnerability. Hence, the bias of being a public programme should result in higher portfolio vulnerability and in reduced client vulnerability. Albeit our results show a marginally higher portfolio vulnerability that could be explained by the public feature of Agroamigo, it also shows a marginally higher clients vulnerability that, instead, compete against the aforementioned bias. In addition, it is important to observe that the recurrent recourse to emergency loans by Agroamigo (see next section), whose funding stems from public coffers and may induce the MFI towards more risky decisions, makes it difficult to use portfolio at risk as proxy for measuring portfolio exposure and vulnerability to CC.

3. SETTING THE CONTEXT

As we have previously stated, poor populations working in agriculture are among the most exposed to CC, and so are the MFIs working with them. Agroamigo operating in Brazil’s Northeast is an emblematic example of such a condition.

Composed of nine states: Bahia (BA), Sergipe (SE), Alagoas (AL), Pernambuco (PE), Paraíba (PB), Rio Grande do Norte (RN), Ceará (CE), Piauí (PI) and Maranhão (MA), Northeastern Brazil is scattered over 1,558,196 km², making up 18.26% of the Brazilian territory. Its coastal area is covered by Atlantic forest whereas its mainland by caatinga, an endemic semiarid climate biome. Albeit famous for its natural beauty, Brazil’s Northeast is most known for its social dimension. In fact, it is one of the poorest regions in the country and where income inequalities – the regional Gini index in 2011 stood at 0.512 (IBGE, 2012) – pose great burden on its people, in particular, on rural communities in the semi-arid areas. 14.5% of the population in the NE earns less than USD 10,000 year (IBGE, 2015) and about 35% of its rural population are in extreme poverty (IFAD, 2011). Lack of adequate basic services, water access stress, harsh climactic conditions, as well sharp income inequalities all place millions of its rural and poor communities in disadvantaged conditions.

It is in this context that in 2005 the Banco do Nordeste do Brasil (BNB) founded Agroamigo as a pilot rural microfinance programme aimed at improving the social and economic conditions of millions of smallholder farmers and rural microentrepreneurs across Brazil’s Northeast, in particular
throughout its semiarid portions – 63% of clients live in the semiarid region (Banco do Nordeste, 2014). In 2013, Agroamigo provided an averaged loan of about US$ 700\(^3\) at interest rates varying between 1% and 5% per year and loan terms between 1 to 10 years depending on the amount, project and/or sector financed (Banco do Nordeste, 2014). Average portfolio risk, measured as portfolio at risk > 30, was as low as 3%, and 90% of its clients had an annual household income of less than US$ 575. As of January 2014, Agroamigo had already disbursed more than US$ 2 billion in microloans in about 2.5 million operations through its 169 branches covering over 1,945 municipalities throughout North-eastern states as well as Minas Gerais (Banco do Nordeste, 2014).

However for its climate specificities and its harsh social conditions, the Northeast Region is placed in the frontline of CC as one of Brazil’s most vulnerable areas to a CC (Baettig, Wild, Imboden, 2007). In the Caatinga biome, covering most part of Brazil’s northeast, surface air temperatures are projected to increase and rainfalls to decrease significantly over the century compared to past trends (last decades of the 20\(^\text{th}\) century). Accordingly, temperatures are likely to increase by 0.5°C and 1°C and rainfalls to decrease by 10% to 20% until 2040. Between 2041 and 2070, the climate in the region will get even warmer, up 1.5°C to 2.5°C, and way drier as rainfalls are expected to decline by between 25% and 35%. In the last three decades of the century, temperatures are likely to increase by as much as 3.5°C to 4.5°C whereas rainfall to decrease markedly by 40% to 50% (PBMC, 2013:27).

In terms of GDP growth, CC will likely affect the North-East (Ecobracc, 2010) with a decrease in GDP growth of about -1% in 2035 and -1.6% in 2050 under the A2 scenario and -2.1% in 2035 and -2.9% by 2050 under the B2 scenario with respect to the annual growth without CC. The most likely affected sector will be agriculture with a reduction in GDP surrounding -1.7% in 2035 and -2.5% in 2050 under A2 and -2.9% and -4.5% under B2 with respect to a CC free scenario.

CC will also impact household wealth by reducing GDP per capita and increasing poverty levels. We do not have data specific for the Northeastern region. However, we believe national level data could be a good proxy to understand such trends in the region. At the national level, the GDP per capita will be reduced by -0.3% in 2035 and -0.5% in 2050 under an A2 scenario, and -1.5% at 2035 and -2.3% by 2050 under B2 with respect to a CC free scenario. As a consequence of CC, poverty is likewise expected to marginally increase by between 0.02% and 0.06% per year at national level under A2 and B2 respectively, with respect to a scenario without CC.

\(^3\) USD - BRL = 2.61(16/11/2014)
Other changes in the climate pattern in the NE include: drier air and increase in the number of consecutive dry days; reduction in extreme rainfall events leading to increased frequency of droughts; increased evapotranspiration; and, eventual sea level rise in coastal areas, especially in the city of Recife (Marengo and Valverde, 2007; Muehe, 2006). The Brazilian Panel on Climate Change (PBMC) suggests that such drastic changes in the climate pattern are likely to trigger major natural and socioeconomic impacts across Northeastern Brazil. In fact, the economy of the region is widely based on agricultural production – 22.5% of population in employment works in the agricultural sector (IBGE, 2015) – [mostly subsistence agriculture] and food products such as cocoa, sugar and cotton and livestock such as cattle breeding, all components that will be hit hard by increased temperature and associated disturbances. Moreover, nearly 500,000 people are likely to migrate towards other regions of the country as result of climate change over the century (Barbieri et al., 2008).

MF operations bear then an additional credit risk associated with the present harsh climate conditions and the forecasted evolution as result of CC. In a previous paper (Moser, Forcella, Gonzalez, 2015), we have discussed the overall exposure to CC of two of the major rural MF programmes in Brazil, among which Agroamigo, and the opportunities for such programmes to establish adapted products. In the following section, we will instead discuss the correlations between credit distribution and vulnerability. The aim is to do a first step toward understanding how present socio-economic and climatic conditions interact with the credit distribution and how that has the possibility to affect future CC related vulnerability of MF and clients.

4. DATA ANALYSIS and MAIN RESULTS

In this section we present our data analysis and main results. According to the 2010 census (IBGE, 2010) the total population in the nine states in the North-East region in Brazil was 53,081,950 in 2010, among which 5,040,152, i.e. the 9.5%, were employed in rural activities. In 2013, the number of BNB’s branches providing credits via Agroamigo were 155, with a cumulated number of disbursed credits for the period 2005-June/2013 of 1,876,863, i.e. more than one credit per every three people employed in a rural activity. The total volume of credit was BRL 3,526,237,000, i.e. more than USD 1 billion, corresponding to an average BRL 1,879 per credit or BRL 700 per person employed in rural activities, i.e. respectively around USD 700 and USD 260. In terms of number of credit disbursed and similarly in credit volume, Agroamigo’s lending has been channeled to four
main activities: 81% in livestock, 12% in agriculture, 1% in extractivism, and 6% in services.

Table 1 reports some demographic data per state and for the nine Northeastern states and the cumulated credit allocation of Agroamigo from 2005 through June 2013.

Table 1: Demographic data and Agroamigo’s cumulated credit allocation from 2005 through June 2013 by NE state.

<table>
<thead>
<tr>
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</tr>
</thead>
<tbody>
<tr>
<td>BA</td>
<td>14,016,906</td>
<td>10.8%</td>
<td>367609</td>
<td>711,301,000</td>
</tr>
<tr>
<td>SE</td>
<td>2,068,017</td>
<td>9.2%</td>
<td>117318</td>
<td>203,106,000</td>
</tr>
<tr>
<td>AL</td>
<td>3,120,494</td>
<td>9.3%</td>
<td>133155</td>
<td>251,106,000</td>
</tr>
<tr>
<td>PE</td>
<td>8,796,448</td>
<td>7.8%</td>
<td>230520</td>
<td>445,933,000</td>
</tr>
<tr>
<td>PB</td>
<td>3,766,528</td>
<td>9.7%</td>
<td>165020</td>
<td>313,012,000</td>
</tr>
<tr>
<td>RN</td>
<td>3,168,027</td>
<td>6.3%</td>
<td>127928</td>
<td>238,751,000</td>
</tr>
<tr>
<td>CE</td>
<td>8,452,381</td>
<td>8.2%</td>
<td>311481</td>
<td>556,174,000</td>
</tr>
<tr>
<td>PI</td>
<td>3,118,360</td>
<td>11.4%</td>
<td>222113</td>
<td>424,895,000</td>
</tr>
<tr>
<td>MA</td>
<td>6,574,789</td>
<td>11.4%</td>
<td>201719</td>
<td>381,959,000</td>
</tr>
</tbody>
</table>

Source: Banco do Nordeste, 2014; IBGE, 2010

Table 2 describes the cumulated credit allocation (from 2005 to June 2013) per state in the various financed activities.
Table 2: Activities financed by Agroamigo as % of total cumulated volume of credit, as of June 2013

<table>
<thead>
<tr>
<th>States (NE)</th>
<th>Livestocks</th>
<th>Agriculture</th>
<th>Fishing and forestry</th>
<th>Services</th>
</tr>
</thead>
<tbody>
<tr>
<td>BA</td>
<td>81.3%</td>
<td>15.8%</td>
<td>1.4%</td>
<td>4.3%</td>
</tr>
<tr>
<td>SE</td>
<td>85.8%</td>
<td>3.4%</td>
<td>0.1%</td>
<td>10.0%</td>
</tr>
<tr>
<td>AL</td>
<td>63.1%</td>
<td>30.2%</td>
<td>2.8%</td>
<td>5.3%</td>
</tr>
<tr>
<td>PE</td>
<td>85.0%</td>
<td>10.5%</td>
<td>0.9%</td>
<td>4.5%</td>
</tr>
<tr>
<td>PB</td>
<td>79.7%</td>
<td>6.3%</td>
<td>0.9%</td>
<td>14.7%</td>
</tr>
<tr>
<td>RN</td>
<td>86.9%</td>
<td>6.5%</td>
<td>1.7%</td>
<td>6.0%</td>
</tr>
<tr>
<td>CE</td>
<td>69.6%</td>
<td>18.8%</td>
<td>1.0%</td>
<td>12.8%</td>
</tr>
<tr>
<td>PI</td>
<td>88.6%</td>
<td>3.1%</td>
<td>2.0%</td>
<td>7.4%</td>
</tr>
<tr>
<td>MA</td>
<td>80.5%</td>
<td>7.3%</td>
<td>8.6%</td>
<td>4.4%</td>
</tr>
</tbody>
</table>

Source: Banco do Nordeste, 2014

According to these data it is clear that Agroamigo is providing loans in key agricultural sectors for an important part of North-eastern rural population. However, it is quite evident that its portfolio is concentrated in few activities, mainly livestock, and in particular, dairy cattle production, that forms more than three-fourth of total cumulated number of credits and total credit volume. Diversification is one of the basic strategies to reduce risk exposure from unknown events and, in particular, from local CC related hazards. Agroamigo’s portfolio concentration in CC vulnerable activities coupled with the fact that its operations are scattered through a weather exposed area constitute an important source of risk to its double bottom line mission, as discussed in (Moser, Forcella, Gonzalez, 2015). In particular, such risk is even higher considering the absence of a clear strategy on water access, the absence of saving products, the very low insurance cover (only a tiny percentage of the outstanding loans) and no tailored strategy to foster more climate adapted practices. The recent droughts in the Northeast (see for instance Calheiros, 2013) have clearly shown the vulnerability of Agroamigo to harsh climatic conditions and related shocks. In the period 2012-2013, certain inner regions experienced exceptional droughts conditions, the livestock market value fell by 28% on average and 50% in certain villages (Pimentel, 2012), leading Agroamigo’s clients to organise protests asking for debt write-offs. To face the harsh situation, the BNB, following a government’s directive, allocated approximately US$1.5 billion in emergency loans: nearly as much as eight-years of loan provision! Such past and current droughts and their dramatic effects clearly show the vulnerability of local populations, clients and MFIs to
forthcoming similar events that are forecasted to increase in intensity and frequency due to local
effects stemming from climate change.

*Grosso modo*, portfolio concentration on weather vulnerable activities may increase the
climatic risk of MF providers and of their clients. Diversification of incoming generating activities,
and incentives for the clients to engage in more adapted practices (through, for example, technical
assistance and specific loan conditions, or insurance for more adapted activities) are two strategies
to reduce portfolio vulnerability and increase clients’ resilience (Hammill et. al. 2008; Rippey,
2012, Dowla, 2009, Forcella, 2013a; Forcella 2013b). Such strategies, on the other hand, would
imply a proactive role of MF providers that should try to stimulate better practices instead of simply
responding to current market demands. Finance and MF *per se*, instead, tends to naturally respond
to the market demand, without directly influencing it. Such behaviour was even more stimulated by
the past and present call for specialisation of microfinance services.

Yet, it is reasonable to believe that in the case of climatic risks, a proactive role would be
beneficial not only for clients, but also for MFIs that would see its covariant credit risks reduced.
On the other hand, CC is always perceived, at best, as a long term risk, and a very uncertain one.
These reasons are important incentives for MFIs not to act, and minimise, in this fashion, their cost
of action. This reasoning could be, however, different for MFIs operating in weather prone areas,
whereby effects of chaining weather conditions or of harsh weather events (related or not to CC) are
already observed, and would then, make climatic risks more salient. A peculiarity of Agroamigo is
that it is funded with public money, as most of Brazilian microfinance players (Soares and Melo,
2008) and hence the approach to such covariant risks could be naturally different, with more
attention to social dimensions.

In parallel to that, family farmers’ rural practices grounded on traditions, culture and local
customs, are known to have a big inertia following development pathways that have been
established by a historical dynamical process (Hidanpaa and Bromley, 2014; Bastiaensen et. al.
2015; Huybrechs et. al., 2015, Forcella and Lucheschi, 2016). Moreover way too often poor rural
producers are at the lowest levels of the value chain of growing food commodity markets, mostly
demand-driven, which limit their level playing field and direct decision possibilities.

From the previous analysis it appears then that, even with its particularities (public, socially
driven), Agroamigo might have encountered difficulties in nudging diversification of local labour
practices and activities irrespective of risks related to the financing of key vulnerable sector and in
areas susceptible to harsh weather conditions, in particular, to intense droughts. However, it is worth
recognising that to cope with such hard conditions and complex socio-economic situations it is
matter of coordinated efforts from many local and national actors, of which MF can be a tool, but not a panacea by itself.

4.1 A State by State analysis

Socio-economic analysis

As an attempt to understand whether the aforementioned trends could also be observed in the various areas of operations of Agroamigo, we looked at the socio-economic indicators and CC vulnerability and credit allocation at in every NE state. With this analysis we aim to better understand how Agroamigo’s credit allocation reflects implicit perception of potential climatic vulnerabilities of its portfolio, or of its clients. By this we do not mean that the actual geographical distribution of Agroamigo’s portfolio has been stimulated by a CC vulnerability reflection or strategy. We understand that the direct and indirect reasons for the geographical distribution of Agroamigo and rural MF in general are multidimensional and usually not primarily or necessarily influenced by weather conditions or forecasted CC events, rather than social needs and economic opportunities. Yet, climate variables do impact local populations, in particular the poor, which in turn, influence the degree of vulnerability and exposure of an MFI itself, based on its spatial distribution.

Looking at the credit distribution for every state we observe that Agroamigo (through 2005-June/2013) disbursed more credits and more credit volume in those states with more people employed in rural activities: with Pearson correlation 0.89 and 0.91 and Spearman correlation 0.87 and 0.87 respectively (see the Figure 1). We interpret this result as supporting evidence that credit allocation followed population needs and market demand in the various states in terms of populations employed in rural activities.
The great bulk of credits and the great amount of the loan portfolio go to states that have the highest GDP accrued in livestock and agriculture, with Pearson correlations 0.72 and 0.75 and Spearman correlation 0.82 and 0.82 respectively (see Figure 2). We interpret this as hint that Agroamigo links its operations with the economic opportunities in rural activities in the various states.

We observe that the number of credits and loan size per person employed in rural activities is higher in states that have the lowest GDP per capita in livestock and agriculture, with Pearson correlation -0.52 and -0.55 and Spearman correlation -0.43 and -0.43 respectively (see Figure 3). In addition, in those states with the highest GDP per capita in agriculture and livestock, such as Maranhão and Bahia, Agroamigo seems to disburse more credit in fewer operations, suggesting that it may be benefitting mostly the better-off among the poor rural population in these two states. Unlike, in states with medium GDP per capita levels in agriculture and livestock, e.g. Sergipe, Alagoas, and Rio Grande do Norte, Agroamigo tends to provide greater amounts of loans of lower sizes, suggesting that it seeks to outreach poorer producers. Overall we look at these data as a hint that the spatial credit distribution of Agroamigo is somehow associated with poverty levels (measured as GDP per capita employed in rural activities) of the various states. In other words, Agroamigo seems to provide more microloans in poorer states.

![Bar Chart: Number and volume of credits disbursed by Agroamigo and population employed in agricultural sectors](image)

Source: Banco do Nordeste, 2014; IBGE, 2010
This preliminary analysis seems then to corroborate previous impact studies, such as (Abramovay et. al, 2013), supporting the thesis that Agroamigo would be indeed fulfilling its social mission.
CC vulnerability analysis

A better look at the states’ CC vulnerabilities, as computed with the CC vulnerability indexes, adds up new variables to the scrutiny in terms of credit allocation patterns. In Table 3 we report the various vulnerability indices per state and according to the two climatic scenarios: A2 and B2, as presented in (Barbieri et al., 2008), and the GVIav computed as the average of the four sub-indices for the various scenarios.

Table 3: Climate change vulnerability indexes for Brazil’s Northeast under A2 and B2 scenarios, 2071-2100 time-scale

<table>
<thead>
<tr>
<th>States in NE</th>
<th>GVlavA2</th>
<th>GVlavB2</th>
<th>SHVI</th>
<th>DVI</th>
<th>CVIA2</th>
<th>CVIB2</th>
<th>EDVIA2</th>
<th>EDVIB2</th>
</tr>
</thead>
<tbody>
<tr>
<td>BA</td>
<td>0.72</td>
<td>0.51</td>
<td>0.73</td>
<td>0.88</td>
<td>1.0</td>
<td>0.0</td>
<td>0.25</td>
<td>0.42</td>
</tr>
<tr>
<td>SE</td>
<td>0.40</td>
<td>0.44</td>
<td>0.56</td>
<td>0.52</td>
<td>0.5</td>
<td>0.67</td>
<td>0.0</td>
<td>0.0</td>
</tr>
<tr>
<td>AL</td>
<td>0.34</td>
<td>0.34</td>
<td>0.13</td>
<td>0.46</td>
<td>0.5</td>
<td>0.67</td>
<td>0.25</td>
<td>0.08</td>
</tr>
<tr>
<td>PE</td>
<td>0.62</td>
<td>0.66</td>
<td>0.0</td>
<td>0.98</td>
<td>0.5</td>
<td>0.67</td>
<td>1.0</td>
<td>1.0</td>
</tr>
<tr>
<td>PB</td>
<td>0.61</td>
<td>0.70</td>
<td>0.7</td>
<td>1.0</td>
<td>0.0</td>
<td>0.33</td>
<td>0.75</td>
<td>0.75</td>
</tr>
<tr>
<td>RN</td>
<td>0.55</td>
<td>0.60</td>
<td>0.46</td>
<td>1.0</td>
<td>0.5</td>
<td>0.67</td>
<td>0.25</td>
<td>0.25</td>
</tr>
<tr>
<td>CE</td>
<td>0.84</td>
<td>0.84</td>
<td>0.66</td>
<td>0.79</td>
<td>1.0</td>
<td>1.0</td>
<td>0.92</td>
<td>0.92</td>
</tr>
<tr>
<td>PI</td>
<td>0.48</td>
<td>0.43</td>
<td>0.4</td>
<td>0.5</td>
<td>0.5</td>
<td>0.33</td>
<td>0.50</td>
<td>0.5</td>
</tr>
<tr>
<td>MA</td>
<td>0.44</td>
<td>0.31</td>
<td>1.0</td>
<td>0.0</td>
<td>0.5</td>
<td>0.0</td>
<td>0.25</td>
<td>0.25</td>
</tr>
</tbody>
</table>

Source: based on Barbieri et al. (2008)

It is quite appealing to plot the various degrees of CC vulnerabilities — along the four dimensions previously presented and in aggregated terms using the GVIav—, against Agroamigo’s credits and portfolio distribution throughout the nine NE states, and compute the respective correlations (see Table 4).

In Table 4, we report the correlations between cumulated number of credits and volume of credits of Agroamigo in the period 2005-June/2013 with respect to the forecasted CC vulnerability in every state along the various dimensions and according to a low and high emission scenarios. As previously explained the correlation between the vulnerability indices and the total number of credits and the total volume of credits is used as a proxy for the relative vulnerability of the Programme, and, in particular, its portfolio, to CC events. In Table 4 is also reported the correlation between the vulnerability indices with the number of credits per person employed in rural activities.
and the average credit per person employed in rural activities per state. As mentioned in the methodology section, we see these correlations as a proxy for the marginal vulnerability to CC of the rural population in the different states in which the MFI under scrutiny operates. A person employed in rural activities living in a state with higher CC or weather related vulnerabilities would need on average greater size and amount of credits to reduce its risk at a level comparable to a peer rural producer living in less vulnerable states.

Table 4 illustrates that Agroamigo had the tendency to provide more credits (both in terms of numbers and size) in the states that will likely be most affected by climate change over the 21st century. As illustrative example, the Pearson correlation between number of credits and total volume of credits per state and GVIav for the most stringent (A2) climate change scenario is respectively 0.77 and 0.75, while it is 0.34 and 0.30 for the low emission scenario (B2). This trend is confirmed also by an analysis of the Spearman correlation that does not test linear collinearity as the Pearson correlation, but sole monotonic correlation, and is less affected by outsiders in the sample. This trend is supported also by the correlations with the four sub-indicators. These data seem to indicate that the geographical allocation of credits by Agroamigo exposes its portfolio to a higher climatic risk. In other words, Agroamigo provides more credits and greater credit size to the population living in states that are more vulnerable to climate change. This tendency reasonably increases the Programmes’s marginal credit CC risk and, in particular, the CC vulnerability of its portfolio and, thus, should be understood and mitigated with the use of adapted products, strategies and policies to keep this additional credit risk at acceptable levels, managing, ultimately, residual CC related risks.

Table 4 also suggests that Agroamigo is, at the same time, providing fewer services to the population that will instead need more support to build up its adaptive capacity. The Programme tend in fact to provide least services per person in the states that are more vulnerable to CC according to the various indices. The correlation between the climate vulnerability indexes and the number of credits or loan size per person employed in rural activities in the various states is almost always negative. As an illustrative example, the Pearson correlation between GVIav under an A2 scenario is -0.32, both for average loan volume and total number of loans per person employed in rural activities. This tendency is strengthened by the Spearman correlation that is indeed -0.45.
Table 4: Pearson/Spearman correlations between CC vulnerability indexes and Agroamigo’s credit data.

<table>
<thead>
<tr>
<th>Correlations: Pearson / Spearman</th>
<th>Num Credits 2005-Jun 2013</th>
<th>Vol Credits 2005-Jun 2013</th>
<th>Num Cr Person in Rural Act</th>
<th>Average Loan Person in Rural Act</th>
</tr>
</thead>
<tbody>
<tr>
<td>GVI A2 av</td>
<td>0.77 / 0.77</td>
<td>0.75 / 0.77</td>
<td>- 0.32 / - 0.45</td>
<td>- 0.32 / - 0.45</td>
</tr>
<tr>
<td>GVI B2 av</td>
<td>0.34 / 0.30</td>
<td>0.30 / 0.30</td>
<td>0.05 / 0.05</td>
<td>0.04 / 0.05</td>
</tr>
<tr>
<td>SHVI</td>
<td>0.25 / 0.20</td>
<td>0.23 / 0.20</td>
<td>- 0.27 / - 0.50</td>
<td>- 0.30 / - 0.50</td>
</tr>
<tr>
<td>DVI</td>
<td>0.19 / 0.03</td>
<td>0.19 / 0.03</td>
<td>0.13 / 0.12</td>
<td>0.15 / 0.12</td>
</tr>
<tr>
<td>CVI A2</td>
<td>0.74 / 0.63</td>
<td>0.70 / 0.63</td>
<td>-0.29 / -0.40</td>
<td>-0.33 / -0.40</td>
</tr>
<tr>
<td>CVI B2</td>
<td>-0.25 / -0.22</td>
<td>-0.30 / -0.22</td>
<td>0.51 / 0.41</td>
<td>0.47 / 0.41</td>
</tr>
<tr>
<td>EDVI A2</td>
<td>0.37 / 0.58</td>
<td>0.36 / 0.58</td>
<td>-0.21 / -0.23</td>
<td>-0.18 / -0.23</td>
</tr>
<tr>
<td>EDVI B2</td>
<td>0.53 / 0.71</td>
<td>0.52 / 0.71</td>
<td>-0.29 / -0.34</td>
<td>-0.26 / -0.34</td>
</tr>
</tbody>
</table>

Source: Authors

Note: In orange we underline the positive correlation trend, while in blue we underline the negative correlations.

These observations are quite simply illustrated by Figure 4. The blue column is the value of the GVIav under the A2 scenario, the green column is the total volume of credits cumulated between 2005 and June/2013 in billions of BRL, the yellow column is the amount of credit per person employed in rural activities in thousands of BRL. We can observe that the blue and green columns are quite positively correlated: on average the higher the vulnerability of a state, the bigger is the portfolio share of Agroamigo invested in that state. While the blue and the yellow columns are instead quite negatively correlated: the higher the vulnerability of a state the lower is the average credit per person working in rural activities in that state.

Figure 4: Agroamigo’s loan portfolio, GVIav and average credit per person in rural activities per NE State

Source: Banco do Nordeste, 2014; IBGE, 2010; authors
We then argue that even if the current geographical distribution of Agroamigo’s loans contributes to increase its climatic risks, it is however not aiming to offset the vulnerability of its clients.

The geographical distribution of credit disbursements is probably induced by the population distribution in the various states and their economic activities, irrespective of local weather patterns. This, though, may generate, as side effect, higher risks for the MFI’s portfolio in states plagued by harsh climate conditions and, at the same time, may contribute less to increase the resilience of the population in the more vulnerable states, compared to the population living in less vulnerable ones. CC will negatively affect rural development in the region and Agroamigo should work to offset or at least mitigate this possibility as this scenario may compromise the achievement of its double bottom line mission. Careful strategies should be implemented to secure its portfolio against climatic forthcoming conditions, and credit should expand to regions where households would need it more to adapt to current and new extreme climatic events, and foster the implementation of more adapted activities and strategies.

**GDP and agricultural land**

To support our previous analysis in this subsection we look at the how the credit allocation of Agroamigo correlated with the forecast GDP and agricultural land variation due to CC.

According to Ecobracc (2010), CC will impact significantly GDP growth in the North-East as presented in Table 5, with a general decrease in the GDP per year with respect to a scenario without CC. This marginal decrease in GDP due to CC events will affect the possibilities of development and vulnerability reduction of NE’s population. As explained in previous sections, the rural poor will be the most affected with a national marginal decrease in GDP in agriculture of -1.7% in 2035 and -2.5% in 2050 under the A2 scenario, and -2.9% and -4.5% in 2035 and 2050 respectively, under a B2 scenario. These values are stronger than in other sectors that will be indeed less affected: industry (services) -0.2% (-0.1%) and -0.3% (-0.4%) in 2035 and 2050, respectively, under A2, and -1.3% (-1.4%) and -2.0% (-2.1%) in 2035 and 2050, respectively, under B2. Moreover a marginal increase in poverty and a marginal decrease in the GDP per capita are expected as discussed in the first section.
Table 5: Decrease in % in the GDP per year with respect to a scenario without CC.

<table>
<thead>
<tr>
<th>State (NE)</th>
<th>Scenario A2</th>
<th>Scenario B2</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>2035</td>
<td>2050</td>
</tr>
<tr>
<td>BA</td>
<td>0,2%</td>
<td>-0,1%</td>
</tr>
<tr>
<td>SE</td>
<td>-0,5%</td>
<td>-1,0%</td>
</tr>
<tr>
<td>AL</td>
<td>-6,2%</td>
<td>-8,2%</td>
</tr>
<tr>
<td>PE</td>
<td>-0,8%</td>
<td>-1,4%</td>
</tr>
<tr>
<td>PB</td>
<td>-1,6%</td>
<td>-2,6%</td>
</tr>
<tr>
<td>RN</td>
<td>-0,8%</td>
<td>-1,4%</td>
</tr>
<tr>
<td>CE</td>
<td>-1,6%</td>
<td>-2,7%</td>
</tr>
<tr>
<td>PI</td>
<td>-0,8%</td>
<td>-1,3%</td>
</tr>
<tr>
<td>MA</td>
<td>-3,8%</td>
<td>-5,5%</td>
</tr>
</tbody>
</table>

Sources: Ecobraccc, 2010.

Table 6 illustrates the correlation between CC impacts on the GDP in the nine states and the historical distribution of credits (2005-Jun 2013).

Table 6: Correlation between CC impacts on GDP and credit distribution per state.

<table>
<thead>
<tr>
<th>Correlations: Pearson / Spearman</th>
<th>Num Credits 2005-Jun 2013</th>
<th>Vol Credits 2005-Jun 2013</th>
<th>Num Cr Person in Rural Act</th>
<th>Average Loan Person in Rural Act</th>
</tr>
</thead>
<tbody>
<tr>
<td>GDP 2035 A2</td>
<td>0.37 / 0.15</td>
<td>0.37 / 0.15</td>
<td>0.16 / 0.03</td>
<td>0.15 / 0.03</td>
</tr>
<tr>
<td>GDP 2050 A2</td>
<td>0.36 / 0.14</td>
<td>0.36 / 0.14</td>
<td>0.18 / 0.07</td>
<td>0.17 / 0.07</td>
</tr>
<tr>
<td>GDP 2035 B2</td>
<td>0.14 / -0.08</td>
<td>0.13 / -0.08</td>
<td>0.15 / 0.03</td>
<td>0.09 / 0.03</td>
</tr>
<tr>
<td>GDP 2050 B2</td>
<td>0.04 / -0.10</td>
<td>0.03 / -0.10</td>
<td>0.17/ 0.00</td>
<td>0.11/ 0.00</td>
</tr>
</tbody>
</table>

Source: Authors

Correlations between decrease in GDP due to CC and the various proxies for credit distribution are all quite weak and make us concluding that in general there is no clear strategy at today to handle with CC impact on economic activities. However, there exist a weak tendency to provide more credits in volume and number in states that will have the GDP less affected by CC,
while the correlation is essentially zero with respect to credits per person. These results imply a marginal tendency to reduce the vulnerability of the portfolio to CC but that will, at the same, do little to support people in regions where CC will hit the hardest.

In Barbieri et. al. (2008) it is reported that the availability of land adapted for agriculture is deemed to decrease due to CC, as presented in Table 7.

Table 7: Reduction of land adapted for agricultural activities

<table>
<thead>
<tr>
<th>Source: Barbieri et. al. (2008)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Note: Variation in % of total between 2010 and 2050 and average between A2 and BA scenario.</td>
</tr>
</tbody>
</table>

This reduction in availability of agricultural land will reasonably affect local adaptation capacity and even more for the poor population. The correlation between such variation and Agroamigo’s cumulated portfolio is presented in Table 8.

Table 8: Pearson and Spearman correlation between land contraction and Agromigo’s cumulated loan portfolio

<table>
<thead>
<tr>
<th>Correlations: Pearson / Spearman</th>
<th>Num Credits 2005-Jun 2013</th>
<th>Vol Credits 2005-Jun 2013</th>
<th>Num Cr Person in Rural Act</th>
<th>Average Loan Person in Rural Act</th>
</tr>
</thead>
<tbody>
<tr>
<td>Land reduction % of total</td>
<td>- 0.31/-0.33</td>
<td>- 0.30/-0.33</td>
<td>0.04/-0.07</td>
<td>- 0.02/-0.07</td>
</tr>
</tbody>
</table>

Source: Authors

Correlations are quite weak, however, it could be observed that in the states in which the risk of reduction of land for agricultural activities is higher, Agroamigo provides more loans and more capital, but at the same time, does not provide more loans and more capital per person employed in rural activities in the most vulnerable states. This fact corroborates our previous conclusions and suggests a marginally higher vulnerability to climate change for the MFI’s portfolio and also its clients.
CONCLUSIONS

In this paper we discussed the CC vulnerability of rural microfinance using the specific case study of the largest rural MF programme in Brazil: Agroamigo. More specifically, we sought to assess how the geographical service/credit allocation influenced the CC vulnerability of an MFI and its clients. From our analysis it emerged that the geographical distribution of services of rural MF programmes operating in drought prone areas could increase their marginal exposure to CC while at the same time not necessarily offsetting the CC vulnerability of the population.

In fact, from our analysis it appears that total rural population and the total rural GDP are factors that increase credit allocation in a given geographical region. However, poorer states, measured in terms of agricultural output per person, received the least amount of credits per person. Using various CC vulnerability indices we observed, moreover, that Agroamigo provided more credits, in terms of total volume and total number of credits, to states that are more vulnerable to CC, potentially increasing its portfolio’s vulnerability to CC and/or weather related impacts. At the same time, Agroamigo also provided less credits per person and less credit amount per person in states with higher vulnerability to CC, leaving the most exposed population potentially more vulnerable to climate change.

Such results call for a better understanding of CC risks and the introduction of tailored strategies for rural microfinance programmes that could, at once, provide more adapted services to the most vulnerable population, while managing eventual climatic risks of microfinance portfolio.

It would be interesting to perform a more in depth analysis of the CC risk for Agroamigo to strengthen or challenge the conclusions of this first study. Moreover it is compelling to perform a similar analysis also for other rural MF programmes so as to better understand whether the observed trends are stand-alone features of Agroamigo or of rural microfinance at large. Understanding the interaction between rural development programmes and CC vulnerability is paramount to better support adaptation strategies and, ultimately, ensure a sustainable provision of products and activities at the microfinance level.
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