

Can Microcredit Help to Cope with Aggregate Shocks? Evidence from Ecuador*

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Abstract

This paper analyzes the effect of natural disasters such as volcanic eruptions on the demand and approval of microfinance loans using data from Banco ProCredit Ecuador. We find that high volcanic activity leads to a significantly higher demand for credit while, at the same time, the probability to receive a loan decreases. Yet, this result holds only for new credit applicants whereas returning clients are equally likely to be approved for loans after volcanic eruptions occurred. The findings suggest that microcredit can have an insurance function, yet only if the relationship with the bank has already been established.

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1 Introduction

Low-income households in developing economies face severe income risks arising both from individual-specific and aggregate shocks. While idiosyncratic shocks such as illnesses or the loss of employment can to some degree be insured within a community, aggregate shocks are more difficult to cope with since natural disasters such as earthquakes, droughts or floods affect every single household in a specific region.

To reduce the impact of income risk, households have developed sophisticated strategies. Morduch (1995) distinguishes between income and consumption smoothing strategies. Income smoothing or risk-management implies that households attempt to choose less risky forms of income generation through diversifying income. However, by reducing fluctuations in income, households often choose less profitable forms of production or employment which can have very costly long-run effects (Morduch 1995, Dercon 2002). Consumption smoothing or risk-coping strategies are concerned with dealing with the consequences of shocks. Important strategies include borrowing through formal or informal mechanisms such as family and friends (Rosenzweig 1988, Dercon 2002) or rotating savings and credit associations (ROSCAs) (Bouman 1995, Besley, Coate and Louny 1993, among others). Furthermore, households can insure themselves by using assets as buffer stocks which they build up in good years and deplete in bad years (Deaton 1991, 1992, Rosenzweig and Wolpin 1993). Risk-coping strategies can also involve an adjustment of the labor supply of the household with the objective of earning extra income (Kochar 1995, 1999).

Despite of these various strategies to reduce the effects of income risk, low-income households in developing economies remain vulnerable to adverse income shocks. This is due to the fact that most of these strategies have proved to be insufficient for insuring consumption completely against income risk. Even though households seem to be able to insure consumption to some degree, much risk remains uninsured (Townsend 1994, 1995, Deaton 1997, Grimard 1997, among others). Especially the poorest households seem to have problems to cope with income shocks. Jalan and Ravallion (1999)

report that the lower the wealth of households in rural China, the closer consumption tracks income, implying that the poorest households are most strongly affected by income shocks. Furthermore, the characteristics of income risk such as the severity, frequency and also predictability determine how well households can deal with income shocks. Gertler and Gruber (2002) evaluate the ability of households to cope with adverse health shocks and find that households in Indonesia are reasonably well able to cope with small transient shocks, but that they can only insure 38 percent of the costs associated with illnesses that severely limit their physical functioning. In a similar context, Alderman (1996) finds that repeated shocks are more difficult to cope with than single or infrequent shocks.

Difficulties to deal with income risk can have strong negative effects on the living conditions of the poor including outcomes such as education or the health of children. Jacoby and Skoufias (1997) find that after adverse income shocks, households in India frequently withdraw their children from school. Similarly, Beegle, Dehejia and Gatti (2003) report that households in Tanzania use child labor as a coping strategy for transitory income shocks. Regarding health, Foster (1995) finds that child growth was significantly negatively affected during and after the major flood of 1988 in Bangladesh.¹ Obviously, these undesirable coping strategies can have negative impacts not only on human capital formation but also on long-run economic growth.

It is usually assumed that access to formal credit and insurance markets can lower the vulnerability of households to income risk (Eswaran and Kotwal 1989, Morduch 1995, 1999, among others). This assumption is supported by the empirical evidence. For instance, Beegle et al. (2003) find that households with access to credit rely less on child labor as a buffer for income shocks.² Gitter and Barham (2007) report that credit constrained households in Honduras have lower educational attainments of children whereas Gertler, Levine and Moretti (2002) find that access to microfinance can help households in Indonesia to cope with adverse health shocks.

However, evidence on the direct effect of income shocks on credit demand and approval and the probability to receive a loan is still scarce. One exception is the study by del Ninno, Dorosh and Smith (2003) who find that

households in Bangladesh borrowed significantly more after a major flood in 1998. They report that for 60 percent of all households, borrowing was the dominant coping strategy. However, they are not able to assess the direct effects of the shock on the individual credit applicant. Thus, further evidence is needed in order to judge whether formal credit opportunities such as microfinance schemes can really help low-income households to cope with aggregate income shocks.

This paper attempts to close this gap by testing whether the demand and approval of microfinance loans by ProCredit Bank in Ecuador was influenced by major aggregate income shocks such as volcanic eruptions. Ecuador is a country that has historically been strongly affected by natural disasters such as earthquakes and volcanic eruptions. The last severe outbreak of the most active volcano Tungurahua took place in August 2006. As a consequence, thousands of people had to be evacuated and farming-dependent households living close to the volcano lost a high percentage of their crops.

We use data from ProCredit Ecuador from January 2002 to August 2007 to test whether these volcanic eruptions have an effect on monthly credit demand and approval. We find that after severe volcanic eruptions, monthly credit demand significantly increases. Credit approval, however, also increases, yet considerably less than the demand for credit. When looking only at clients who have received a loan from ProCredit previously, the results indicate that the demand for credit increases as well, yet, in this case, credit approval increases more than the demand for loans.

In order to address the question how volcanic activity affects the individual credit applicant, we analyze in a second step whether the probability that households in the affected areas receive a loan from ProCredit is also influenced by volcanic eruptions. Our results suggest that high volcanic activity in the last months before the credit application leads to significant decreases in the probability to be approved for a loan. This finding, however, holds only for applicants who have not received a loan from this bank previously. Our results indicate that returning clients do not only have a higher probability to receive a loan in general, but that they are equally likely to be approved for a loan after volcanic shocks occurred which implies that compared to new

applicants, the difference in probabilities even increases. The results are robust to using different indicators for volcanic activity, i.e. volcanic explosions or the seismic activity of the volcano, and varying regional samples.

The finding that the demand for credit increases significantly after severe volcanic eruptions occurred can be explained by more households being in need of financing after they were hit by a shock. Yet, since households who apply for loans after these shocks occurred are likely to have on average less financial resources and collateral and probably also due to limited resources of the bank, ProCredit will not be able or will not want to completely meet the demand for credit. However, the finding that clients who have received a loan from ProCredit previously are equally likely to receive a loan after high volcanic activity despite of the increased credit demand can be interpreted as a support for the relationship banking theory arguing that banks develop close relationships with borrowers over time in order to overcome problems of asymmetric information.³ This implies that microcredit can have an insurance function, yet only for those households who have already established a relationship with the bank.

Despite of the positive effect for old clients, the results also imply that besides of microcredit, other measures such as microsaving and microinsurance products are needed in order to help those households cope with aggregate income shocks who did not have access to formal financing previously.

The remainder of the paper is organized as follows. Section 2 presents the theoretical framework and some hypotheses. Section 3 discusses the data we use and gives some descriptive statistics. The econometric models employed are presented in Section 4 while Section 5 is concerned with the empirical results. Finally, Section 6 closes the argument.

2 Theoretical Framework

Aggregate income shocks such as natural disasters can have various effects on the well-being of low-income households. Expressed in the simplest terms, a disaster can affect assets (direct damages), the flow for the production of goods and services (indirect losses), and the performance of the main

macroeconomic aggregates of the affected country (macroeconomic effects).⁴ Direct damages such as the destruction of physical infrastructure usually occur at the moment of the disaster while the latter two types of losses can extend over a period of up to five years (Economic Commission for Latin America and the Caribbean (ECLAC) 2003).

Low-income households are particularly prone to income risk arising from natural disasters. This is due to the fact that they have a higher exposure to disaster risk than other population groups since their choices where to live and in which sector to work are usually limited. Furthermore, due to limited financial resources these households also have a lower risk coping capacity leading to an even higher vulnerability to income risk. It is clear that under these circumstances, borrowing from informal and formal sources such as microfinance institutions (MFIs) is one possible coping strategy for low-income households and microentrepreneurs. A loan can not only bridge the liquidity gap, but also provide the necessary funds for restoring production capacity. Therefore, we argue that after adverse income shocks, the demand for loans should increase.

Hypothesis 1: *After aggregate income shocks, the number of loans demanded increases.*

Even though microcredit could help to bridge liquidity gaps, MFIs still have to consider resource and profitability constraints to ensure financial sustainability. Of course, these constraints can be prohibitive for meeting the additional demand for loans after natural disasters occurred.

First, it is likely that the average risk of each credit applicant is considerably higher since the productivity of households will be affected by the destruction of assets and their ability to generate income will be lower due to market disruptions and higher prices of production inputs. Furthermore, if households have to take out additional loans, higher indebtedness could lead to difficulties in managing liquidity and assuring repayment while, at the same time, these factors will complicate the risk assessment by the MFI (Pantoja 2002).

Second, MFIs are likely to face liquidity crunches during natural disasters since clients will withdraw their savings or save less and others will miss loan payments or will apply for emergency or recovery loans. If these demands occur simultaneously, they will result in liquidity shortfalls for unprepared MFIs, especially if the client pool is not well diversified (Miamiadian, Arnold, Burritt and Jacquand 2005). Therefore, in order to maintain profitability, MFIs will have to restrict lending implying that the additional demand for credit will not be completely met by the bank.⁵

Hypothesis 2: *After aggregate income shocks, the probability to receive a loan decreases.*

However, this lending constraint is unlikely to affect each applicant equally. MFIs usually aim at establishing long term relationships with their clients in order to accumulate information about the borrowers' quality and thereby overcome problems of asymmetric information. They typically use progressive lending mechanisms and non-refinancing threats in order to minimize losses and identify good quality borrowers (Armendáriz de Aghion and Morduch 2005). This relationship banking allows intertemporal transfers between the microentrepreneur and the relationship lender. Being aware of the borrowers' quality, the bank may subsidize the firm in times of financial distress and can offset these losses by extracting higher rents in future periods (Petersen and Rajan 1995). Therefore, MFIs are unlikely to restrict lending to old customers after aggregate shocks occurred. This implies that the probability to receive a loan will either be unaffected or rise for returning clients, but will decrease considerably for new credit applicants.

Hypothesis 3: *After aggregate income shocks, old costumers are equally or more likely to receive a loan and compared to new applicants, the difference in probabilities increases.*

3 Description of the Data

For our analyses we use data from ProCredit Bank Ecuador from January 2002 to August 2007. ProCredit Ecuador was founded in October 2001 and

received a full banking license in 2005. The bank is part of ProCredit Group which consists of 22 banks operating in transition economies and developing countries in Eastern Europe, Latin America and Africa and is led by ProCredit Holding AG, a holding company based in Germany. The group focuses on providing financing for small and medium sized enterprises and follows a profit oriented development banking approach based on financial institution building. At the end of 2007, ProCredit Ecuador was operating 25 branches throughout the country and had granted approximately 58,000 loans with a total amount of \$166 million.⁶

The data we use was generated using the financial management system of ProCredit Ecuador and provides detailed information on loan applicants as well as clients for all branches of the bank. In order to analyze the effects of major aggregate shocks on low-income households we combine the data from ProCredit Ecuador with monthly data on the seismic activity and eruptions of the most active volcano Tungurahua provided by the Instituto Geofísico Ecuador.

Table 1: Summary Statistics of Credit Applicants

	Ambato & Riobamba	All Branches
<i>Demographic Characteristics</i>		
Male (%)	68.20	65.09
Average Age (years)	39.1	38.4
Married (%)	76.30	75.46
<i>Destination of loan</i>		
Agriculture (%)	31.50	19.65
Business/Trade (%)	28.85	35.25
Livestock/Fish Breeding (%)	4.05	6.92
Production/Construction (%)	15.03	18.91
Transportation (%)	9.75	7.64
Observations	48,736	109,354

Ecuador is a country that has historically been strongly affected by natural disasters such as earthquakes and volcanic eruptions. Sitting atop five tectonic plates, the whole region of Latin America and the Caribbean is prone to intense seismic activity. Regarding active volcanoes, Ecuador has the second largest number in the region after Chile (Charvériat 2000). The last severe outbreak of Tungurahua took place in summer 2006. Even though

the eruptive process started already in 1999 and various smaller outbreaks were recorded, the 2006 eruption was the most severe since the last significant period of activity from 1916 to 1925.⁷ During the eruption, pyroclastic flows went downhill threatening various smaller communities located at the base of the volcano. The 10 km high eruptive column was blown west and covered vast areas of the two provinces closest to the volcano, Chimborazo with the capital Riobamba and Tungurahua with the capital Ambato. Approximately 19,000 people had to be evacuated and the Ministry of Agriculture and Livestock reported that about 23,000 hectares of crops had been destroyed due to massive ash fall and that livestock experienced serious health problems from grazing in ash-covered pastures.

Figure 1: Loan Applications and Approvals

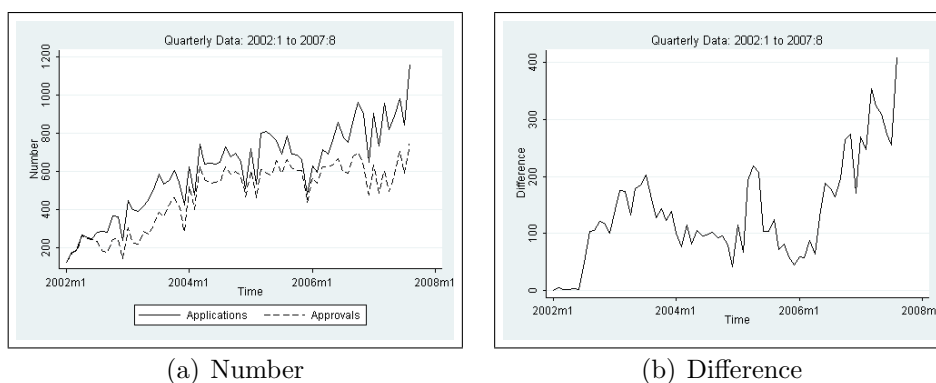


Table 1 summarizes key demographic characteristics of loan applicants as well as typical destinations of loans for the whole period from January 2002 to August 2007. Since the two provinces closest to the volcano, Chimborazo and Tungurahua, were most strongly affected by the eruptions we focus our main analysis on the ProCredit branches operating in their capitals, i.e. Riobamba and Ambato. However, as a robustness check we always compare the results to the effects on all branches in the Andean region.⁸ We have 48,736 observations for Ambato and Riobamba and 109,354 for all branches located in the Andes. Table 1 shows that the majority of credit applicants is male and married and that the difference between Ambato and Riobamba on the one side and all branches taken together on the other side is not high regard-

ing demographic characteristics. However, when it comes to the destination of loans, it is obvious that Ambato and Riobamba have a stronger focus on agriculture compared to the other regions. When looking only at the other Andean provinces, the percentage of loans directed to the agriculture sector even drops to 10.13 percent with the difference between the areas being statistically significant at the 1 percent level.⁹

In order to get an idea about the development of loan applications as well as approvals over time, Figure 1a shows the development of the two variables for the branch of Ambato.¹⁰ As can be seen in the figure, loan applications as well as approvals have been fluctuating over the years, but the positive trend in both variables is clearly visible. It is interesting to observe, however, that the spread between applications and approvals has become wider in the last years (Figure 1.b). This shows that the demand for credit has grown faster than the bank was able or willing to respond to by also granting more loans.

The financial information about the loans is summarized in Table 2. It is clearly observable that the loan amount as well as the maturity applied for have, on average, increased over time. This holds for Ambato and Riobamba as well as for all branches located in the Andes. However, what is more interesting is that the amount applied for has, on average, always been considerably higher than the amount approved.¹¹ The same result holds for the maturity. The maturity applied for is always higher than the maturity approved. These findings are intuitive since higher loan amounts and longer maturities imply higher risk for the bank as well. However, these findings indicate that loan demand is not completely met by the bank, one explanation being that households do not have sufficient collateral or guarantees for receiving the amount or maturity they applied for.

It can also be seen in the table that the percentage of old clients applying for a loan, i.e. households who have already received a loan from this bank previously, is at about 50 percent. That the percentage of old clients actually receiving a loan is considerably higher than the percentage of those applying for credit can be explained by the lower risk those households pose to Pro-Credit. The fact that the bank already has detailed information about the applicants' background as well as repayment behavior clearly works to the

Table 2: Financial Information (Averages)

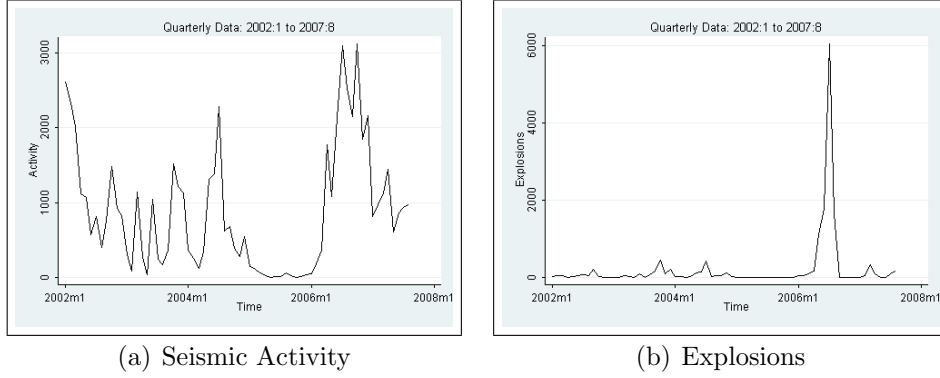
	2002	2003	2004	2005	2006	2007
Ambato & Riobamba						
<i>Credit Amount (\$)</i>						
Amount Applied for	2,513	2,864	2,801	3,405	3,586	3,991
Amount Approved	2,185	2,508	2,617	3,094	3,404	3,705
<i>Maturity (months)</i>						
Maturity Applied for	11.1	13.2	14.3	16.3	17.8	19.6
Maturity Approved	10.4	12.3	13.6	15.6	17.1	19.1
<i>Old Clients (%)</i>						
Applied	21.54	34.37	47.63	58.94	47.98	41.68
Approved	22.10	38.66	51.19	64.88	59.42	58.78
No. Applications	3,069	5,863	7,671	8,403	11,946	11,784
No. Approvals	2,462	3,968	6,589	7,016	8,754	6,754
All Branches						
<i>Credit Amount (\$)</i>						
Amount Applied for	2,165	2,436	2,425	2,572	2,921	3,143
Amount Approved	1,855	2,079	2,209	2,310	2,738	2,933
<i>Maturity (months)</i>						
Maturity Applied for	11.7	13.1	13.7	14.4	16.0	17.6
Maturity Approved	11.0	12.2	13.2	13.8	15.5	17.2
<i>Old Clients (%)</i>						
Applied	18.24	35.14	48.63	52.71	56.29	50.49
Approved	20.30	41.06	52.99	60.54	65.50	63.43
No. Applications	5,527	12,278	16,182	21,981	27,621	25,765
No. Approvals	4,374	9,077	13,607	17,255	20,068	15,608

Notes: [1]Reported credit amounts were deflated to 2002 prices (Source: CIA World Fact Book). [2]Figures for 2007 refer to the time from January to August.

advantage of the households and it seems as if households who have managed to receive and repay a loan at least once have less problems to receive follow-up financing.

Figure 2 displays the seismic activity and eruptions of Tungurahua over time. Figure 2.a shows that the seismic activity has varied considerably over the years with a peak in mid 2006 when the severe outbreak of the volcano occurred. This is even more apparent in Figure 2.b which depicts volcanic eruptions over time. The figure shows very clearly how severe the outbreak was compared to the years before and after this shock.

Figure 2: Seismic Activity and Explosions of Tungurahua



4 Econometric Model

In order to estimate the effect of volcanic activity on low-income households and microfinance institutions we employ different econometric approaches. First, for analyzing the effect of volcanic eruptions on monthly credit demand and approval over time we use a time series model.¹² The time series depicted in Figures 1 and 2 have to be stabilized first by using first differences, since, as is already apparent at least in Figure 1, the data series is non-stationary. This conclusion is also supported by the Dickey-Fuller and Phillips-Perron tests for stationarity. Having stabilized the time series, we identify the most adequate ARMA model specification by analyzing the autocorrelation (ACF) and partial autocorrelation functions (PACF) and testing different ARMA models using the AIC and BIC criteria. The results suggest that an AR(1,12) model outperforms all other specifications. Therefore, we estimate the following OLS model

$$C_t = \theta + \mu_1 C_{t-1} + \mu_2 C_{t-12} + \phi_1 S_t + \dots + \phi_6 S_{t-5} + v_t, \quad t = 1, \dots, T \quad (1)$$

where C_t is monthly credit demand or approval. C_{t-1} and C_{t-12} are the relevant autoregressive terms and S_t to S_{t-5} correspond to the different lags of volcanic activity which are equal to monthly volcanic explosions. Since the variables are used in first differences, S_t to S_{t-5} include six lags of the shock variables which are used in order to account for different effects over time.¹³

Finally, v_t is the error term. In order to estimate the effect of volcanic eruptions on monthly credit demand and approval for returning clients only we use a very similar model. However, the AIC and BIC criteria suggest that in this case an AR(1,2,12) model is the appropriate ARMA model specification.

Second, in order to analyze the effect of volcanic eruptions on the probability to receive a loan we use a probit model since the credit approval decision is a binary-choice variable. However, in order to compare different econometric approaches, we also estimate the effects using a linear probability model (LPM). The according latent variable model can be written as

$$Y_i^* = \alpha + S_i\beta + X_i\delta + L_i\gamma + \epsilon_i, \quad i = 1, \dots, N \quad (2)$$

with the observed variable

$$Y_i = 1\{Y_i^* > 0\}. \quad (3)$$

The dependent variable Y_i equals one if the credit applicant has received a loan and zero otherwise. The vector S_i contains the aggregate shocks. In this specification, different indicators for volcanic activity are compared. Therefore, S_i is either monthly volcanic explosions or the seismic activity of the volcano at the time of the credit application. We use up to six lags of the shock variables in this specification as well. However, since the results do not change when using the sum of the individual shock variables, we will usually refer to these estimates since they are easier to interpret. X_i is a vector of demographic characteristics such as age, marital status and gender. The vector L_i comprises loan characteristics such as the credit amount applied for and an indicator whether households have received a loan from ProCredit previously. Furthermore, destination of loan, region, and year dummies are included in the regression. Finally, ϵ_i is the error term.

5 Estimation Results

The results of the time series regression of monthly credit demand and approval on the autoregressive terms and the number of volcanic explosions in the last six months are summarized in Table 3.¹⁴

Table 3: Time Series Regressions for Monthly Credit Demand and Approval

Variable	Demand	Approval
<i>Autoregressive Terms</i>		
L1.	-0.4796*** (0.1492)	-0.4593*** (0.1179)
L12.	0.5013*** (0.1569)	0.5226*** (0.1454)
<i>Volcanic Activity</i>		
Explosions	0.0080 (0.0081)	0.0005 (0.0043)
L1.	-0.0207** (0.0082)	-0.0169*** (0.0046)
L2.	0.0008 (0.0062)	0.0028 (0.0047)
L3.	0.0247*** (0.0056)	0.0173*** (0.0051)
L4.	0.0198*** (0.0074)	0.0059 (0.0057)
L5.	-0.0112 (0.0074)	-0.0024 (0.0064)
Observations	55	55
F-Test for Volcanic Activity	20.94	19.30

Notes: [1]OLS regression for Ambato with robust standard errors. [2]***denotes significant at the 1 percent level, **at the 5 percent level, and *at the 10 percent level. [3]Standard errors in parentheses. [4]Variables are in first differences.

When looking at credit demand, it can be seen that the first, third and fourth lag have the highest effects while only the first and third lag are significant for credit approval. Yet, the F statistic in both regressions suggests that the lagged terms for volcanic activity are jointly significant at the 1 percent level. Furthermore, the results show that households need some adjustment time after volcanic eruptions occurred since the positive effects become only significant after three months. In contrast, the negative sign on the first lag suggests that volcanic activity, at first, leads to a decrease in credit demand

and approval. When calculating the combined effect of volcanic activity on credit demand as well as approval we find that both effects are positive, yet the impact on demand is stronger than the approval effect.¹⁵

Table 4: Time Series Regressions for Monthly Credit Demand and Approval - Returning Clients

Variable	Demand	Approval
<i>Autoregressive Terms</i>		
L1.	-0.8086*** (0.2018)	-0.6684*** (0.1384)
L2.	-0.3829*** (0.1412)	-0.2788** (0.1126)
L12.	0.5880*** (0.2203)	0.6392*** (0.1729)
<i>Volcanic Activity</i>		
Explosions	0.0050 (0.0033)	0.0032 (0.0042)
L1.	-0.0212*** (0.0032)	-0.0174*** (0.0041)
L2.	0.0056 (0.0042)	0.0103*** (0.0039)
L3.	0.0153*** (0.0037)	0.0155*** (0.0046)
L4.	0.0076 (0.0056)	0.0058 (0.0051)
L5.	0.0019 (0.0051)	0.0063 (0.0050)
Observations	55	55
F-Test for Volcanic Activity	39.62	20.34

Notes: [1]OLS regression for Ambato with robust standard errors. [2]***denotes significant at the 1 percent level, **at the 5 percent level, and *at the 10 percent level. [3]Standard errors in parentheses. [4]Variables are in first differences.

Table 4 summarizes the results of the time series regression of monthly credit demand and approval on the autoregressive terms and the number of volcanic explosions only for those clients who have received a loan from Pro-Credit previously. As can be seen, in this specification only the first and third lag are significant for credit demand while credit approval is also significantly affected by the second lag of volcanic explosions. However, the F-statistic suggests again that the lagged terms for volcanic activity are jointly significant at the 1 percent level. Similar to the findings in Table 3, the negative

sign on the first lag indicates that, at first, credit demand and approval are negatively influenced by volcanic activity while the effects become positive later on. Interestingly, the combined effect of volcanic explosions on credit demand and approval suggest that both effects are positive, yet that in this specification, the effect on credit approval is stronger than for demand.¹⁶

The estimation results of the probit regression of the credit approval decision on the covariates is summarized in Table 5. The first two columns depict the estimation results for Ambato and Riobamba using two different indicators for volcanic activity, i.e. the number of volcanic explosions and the seismic activity of the volcano in the last six months. Correspondingly, as a robustness check, columns (3) and (4) summarize the regression results when using all branches located in the Andean region.¹⁷

The results suggest that a higher number of explosions as well as higher seismic activity in the last six months leads to a lower probability to be approved for a loan. The effects are equally strong in all four regressions. For instance, when considering a one standard deviation increase in explosions in regression (1), the effect implies a decrease in the probability to receive a loan of 4.8 percent. The results are the same when using the different time lags of volcanic activity individually. The results of regression (1) with the different lags of explosions are displayed in Table A2 in the Appendix. It can easily be seen that the lags are highly significant as well and they are also jointly significant at the 1 percent level. Yet, since the aggregate estimates are easier to interpret and the results do not change when using the time lags individually we will refer to these results in the following.¹⁸

Table 5 also shows that the age of the applicant seems to have a negative but also nonlinear effect on the credit approval decision. Marriage, on the other side, increases the probability to receive a loan by about 4 percent. Interestingly, but not surprisingly, men have a lower probability to receive a loan than women. This can be explained by the fact that women are assumed to be more reliable when it comes to the repayment of loans (Hossain 1988, Hulme 1991). When looking at the effect of the credit amount applied for, it can be seen that the higher the amount the lower the probability to receive the loan which can be explained by the higher risk of increasing loan amounts.

Table 5: Probit Regressions for Credit Approval

Variable	Ambato & Riobamba		All Branches	
	(1)	(2)	(3)	(4)
<i>Volcanic Activity</i>				
Explosions	-0.0013*** (0.0001)		-0.0229*** (0.0024)	-0.0261*** (0.0019)
Seismic Activity		-0.0009*** (0.0001)		
<i>Demographic Characteristics</i>				
Age	-0.0045*** (0.0012)	-0.0045*** (0.0012)	-0.0017** (0.0008)	-0.0018** (0.0008)
(Age) ²	0.0000*** (0.0000)	0.0001*** (0.0000)	0.0000** (9.11e-06)	0.0000** (9.12e-06)
Married	0.0400*** (0.0052)	0.0398*** (0.0052)	0.0417*** (0.0034)	0.0418*** (0.0034)
Male	-0.0320*** (0.0045)	-0.0324*** (0.0045)	-0.0334*** (0.0029)	-0.0337*** (0.0029)
<i>Loan Characteristics</i>				
Amount Applied For	-1.47e-06*** (2.44e-07)	-1.48e-06*** (2.44e-07)	-2.85e-06*** (1.97e-07)	-2.86e-06*** (1.97e-07)
Old Client	0.2270*** (0.0048)	0.2122*** (0.0072)	0.2195*** (0.0031)	0.2057*** (0.0038)
Old Client*Explosion	0.0012*** (0.0001)		0.0266*** (0.0031)	
Old Client*Seismic Activity		0.0008*** (0.0001)		0.0246*** (0.0021)
Observations	47,477	47,477	107,643	107,643

Notes: [1]Probit regressions reporting marginal effects. [2]***denotes significant at the 1 percent level, **at the 5 percent level, and *at the 10 percent level. [3]Region, year, and destination of loan dummies included. [4]Standard errors in parentheses.

Table 6: LPM for Credit Approval

Variable	Ambato & Riobamba (1)	(2)	All Branches (3)	(4)
<i>Volcanic Activity</i>				
Explosions	-0.0013*** (0.0001)		-0.0266*** (0.0028)	
Seismic Activity		-0.0012*** (0.0001)		-0.0301*** (0.0020)
<i>Demographic Characteristics</i>				
Age	-0.0040*** (0.0011)	-0.0041*** (0.0011)	-0.0013* (0.0007)	-0.0013* (0.0007)
(Age) ²	0.0000*** (0.0000)	0.0000*** (0.0000)	0.0000** (8.68e - 06)	0.0000** (8.67e - 06)
Married	0.0405*** (0.0048)	0.0403*** (0.0048)	0.0429*** (0.0032)	0.0429*** (0.0032)
Male	-0.0335*** (0.0043)	-0.0340*** (0.0043)	-0.0337*** (0.0028)	-0.0339*** (0.0028)
<i>Loan Characteristics</i>				
Amount Applied For	-1.37e - 06*** (2.45e - 07)	-1.38e - 06*** (2.46e - 07)	-2.69e - 06*** (2.36e - 07)	-2.70e - 06*** (2.36e - 07)
Old Client	0.2103*** (0.0046)	0.1649*** (0.0064)	0.2075*** (0.0029)	0.1863*** (0.0036)
Old Client*Explosion	0.0011*** (0.0001)		0.0280*** (0.0031)	
Old Client*Seismic Activity		0.0010*** (0.0001)		0.0265*** (0.0021)
Observations	47,477	47,477	107,643	107,643
R ²	0.1626	0.1639	0.1329	0.1341

Notes: [1]OLS regressions with robust standard errors. [2]***denotes significant at the 1 percent level, **at the 5 percent level, and *at the 10 percent level. [3]Region, year, and destination of loan dummies included. [4]Standard errors in parentheses.

The indicator whether the applicant is a returning client has the strongest effect on the credit approval decision. The probability to receive a loan increases by about 22 percent compared to new credit applicants. Interestingly, the interaction effects between volcanic activity and the old client indicator are positive and highly significant in all regressions as well.¹⁹ Since the coefficients on the indicator for volcanic activity and the interaction effect have approximately the same size, this implies that old clients are equally likely to receive a loan after they were hit by a shock and that compared to new applicants, the difference in probabilities even increases. Since it is likely that all applicants will have suffered from the shock, this finding can be interpreted as microcredit having an insurance function at least for clients who have already established a relationship with the bank.²⁰

The results of the LPM are summarized in Table 6. Similar to the estimates of the probit regression, the results suggest that higher volcanic activity leads to a lower probability to be approved for a loan, yet again only for new credit applicants. Returning clients are equally likely to receive a loan after volcanic shocks in this specification as well. In addition, the R^2 suggests that the regressions for Ambato and Riobamba have a higher goodness of fit with 16 percent compared to 13 percent for all branches. This is not surprising given the fact that Ambato and Riobamba are likely to be most strongly affected by volcanic eruptions. In contrast, according to the R^2 , the difference between the two indicators for volcanic activity is not high.

6 Conclusion

Poor households in developing countries face substantial income risks which they handle with sophisticated risk-management and risk-coping strategies. However, despite of these mechanisms, low-income households remain vulnerable to income shocks which can have strong negative effects on the living conditions of the poor including household outcomes such as health or education.

Access to formal credit markets is usually assumed to contribute positively to a lower vulnerability of households to income risk. However, there

has not been a lot of evidence on the direct effect of income shocks and, in particular, of aggregate shocks which affect all households in a specific region, on the demand and approval of credit and the probability to receive a loan from microfinance institutions. Yet, in order to judge whether microcredit can indeed help low-income households to cope with income risk, more evidence is needed on this issue.

This paper addressed this question by testing whether the probability to receive a loan from ProCredit Bank in Ecuador is influenced by the volcanic activity of the most active volcano Tungurahua. The main findings of the analyses are that higher volcanic activity leads to a significantly lower probability to be approved for a loan. This finding can be explained by increased credit demand which will not be completely met by the bank. This result, however, holds only for applicants who have not received a loan from ProCredit previously. Clients who already have established a relationship with the bank are about equally likely to receive a loan after volcanic eruptions occurred and compared to new applicants, the difference in probabilities even increases supporting the relationship lending theory. This result implies that old clients who always behaved diligently can count on the bank for assisting them after they were hit by severe shocks. Therefore, in this case, microcredit does have an insurance function, yet only for those who managed to receive a loan from this bank previously.

The results show that microcredit schemes can have an insurance function, yet it depends on the relationship between the microfinance institution and the applicant. While returning clients can count on the bank after they were affected by major shocks, new applicants have to rely on other coping strategies which are likely to be more expensive and less efficient. This implies that other measures such as microsaving and microinsurance products are needed as well since microcredit alone is not sufficient for helping those households cope with aggregate income shocks who did not have access to formal financing previously.

Notes

¹For further evidence on the effects of income shocks on schooling and health outcomes see, for instance, Rose (1999), Jensen (2000), Carter and Maluccio (2003) and Gitter and Barham (2007).

²The observation that inefficiently high child labor can arise due to capital market imperfections has already been documented in early theoretical work by Baland and Robinson (2000) and Ranjan (2001).

³See Boot (2000) for an overview on relationship banking.

⁴The actual impact of the disaster depends, of course, on the nature of the shock and the economic sector affected. In the case of volcanic eruptions, direct effects on the manufacturing sector are rare since volcanoes are usually situated in rural areas. The impact on the agricultural sector, however, depends on the magnitude of the eruption. While ash falls and toxic gases cause only temporary damage in the case of small eruptions, full production recovery might be impossible after strong volcanic activity. Furthermore, if physical infrastructure such as roads are damaged, this can have indirect effects on other sectors such as the commercial, transportation or tourism sector as well.

⁵Even if liquidity management is successful, a profit-oriented MFI could have to restrict lending in times of crises. For instance, if refinancing conditions for additional funds become more costly, MFIs have to earn a higher return on the loan portfolio which would imply that lending standards have to rise (Holmstroem and Tirole 1997).

⁶See <http://www.bancoprocredit.com.ec> and <http://www.procredit-holding.com> for more information.

⁷See the website of the Instituto Geofísico Ecuador (<http://www.igepn.edu.ec>) for more information.

⁸We restrict our analysis to the highlands since, first of all, the whole region is relatively comparable with respect to landscape and the structure of the economy and second, it is unlikely that the coastal areas were affected by eruptions of the volcano. The other provinces included in the analysis are Cotopaxi with the capital Latacunga, Imbabura with the cities Ibarra and Otavalo, and Pichincha with Cayambe.

⁹The summary statistics for credit approvals are relatively similar to Table 1 and are therefore not discussed in detail. For the figures please refer to Table A1 in the Appendix.

¹⁰We restrict the analysis here to Ambato due to the fact that the branches were opened in different years which could lead to misinterpretations if the data was analyzed together and since Ambato is one of the branches being most affected by volcanic shocks.

¹¹For a better comparability, the amount and maturity applied for are summarized only for future approvals.

¹²Monthly credit demand and approval refer to the number of loan applications and approvals, respectively.

¹³We use six lags of volcanic activity since we assume that after six months, the effect

of the shock is likely to die out. Households would have gone to the bank earlier if they were indeed affected by the shock and were in need of financing. However, a shorter time frame might be appropriate as well, yet not less than three months since households need some adjustment time before being able to apply for a loan. Even though the results are not presented in detail here, it should be noted that they do not change considerably when using less than six time lags.

¹⁴In this regression we focus again on Ambato for the same reasons given above.

¹⁵The combined effect of volcanic activity calculated as the sum of the individual coefficients is 0.0214 for credit demand and 0.0071 for approval.

¹⁶The combined effect of volcanic activity is equal to 0.0143 for credit demand and 0.0238 for approval.

¹⁷Since the branches are located in areas affected differently by the volcano, we adjust the indicators for volcanic activity by using the distance to the volcano. This adjustment is not needed in the regressions for Ambato and Riobamba since they are equidistant from the volcano. However, all indicators for volcanic activity have additionally been divided by 100 in order to allow for an easier interpretation of the rather small coefficients.

¹⁸The estimation results of the other regressions can be obtained from the authors upon request.

¹⁹The marginal effects reported in the table had to be calculated separately since the cross derivatives can not be deduced directly from the regression output. See Ai and Norton (2003) for details.

²⁰The finding is in line with the results of other empirical studies concerning the insurance function of relationship banking. See, for example, Elsas and Krahnert (1998).

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Appendix

Table A1: Summary Statistics of Credit Approvals

	Ambato & Riobamba	All Branches
<i>Demographic Characteristics</i>		
Male (%)	68.15	64.81
Average Age (years)	39.4	38.6
Married (%)	78.86	77.81
<i>Destination of loan</i>		
Agriculture (%)	33.31	20.36
Business/Trade (%)	26.25	33.27
Livestock/Fish Breeding (%)	4.16	7.19
Production/Construction (%)	15.51	19.73
Transportation (%)	10.31	8.00
Observations	35,543	79,989

Table A2: Probit Regression for Credit Approval - incl. Lags

Variable	Coefficient	(Std. Error)
<i>Volcanic Activity</i>		
Explosions	-0.0021***	(0.0003)
L1.	-0.0013***	(0.0003)
L2.	-0.0012***	(0.0003)
L3.	-0.0013***	(0.0002)
L4.	-0.0020***	(0.0002)
L5.	-0.0030***	(0.0003)
L6.	0.0013***	(0.0002)
<i>Demographic Characteristics</i>		
Age	-0.0045***	(0.0012)
(Age) ²	0.0001***	(0.0000)
Married	0.0389***	(0.0052)
Male	-0.0314***	(0.0045)
<i>Loan Characteristics</i>		
Amount Applied For	-1.46e - 06***	(2.44e - 07)
Old Client	0.2448***	(0.0042)
Observations	47,477	

Notes: [1]Probit regressions for Ambato & Riobamba reporting marginal effects. [2]***denotes significant at the 1 percent level, **at the 5 percent level, and *at the 10 percent level. [3]Region, year, and destination of loan dummies included.