Natural Disasters and Credit Supply Shocks in Developing and Emerging Economies

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Natural Disasters and Credit Supply Shocks in Developing and Emerging Economies

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Abstract

This research demonstrates that natural disasters are systemic risks for financial intermediaries in developing and emerging economies. We develop a microeconomic mechanism that partially explains macroeconomic evidence that the net effect of a disaster on growth is significantly determined by the capacity of an economy to reinvest after an event. We model a representative, dynamically optimizing lender managing a stock of equity capital and apply it to a microfinance intermediary in Peru that is vulnerable to El Niño-related flooding. The results show that disasters lead to large loan losses that cause lenders to contract credit after the event, slowing recovery for the affected economy. This research also evaluates an insurance-like mechanism to be purchased by financial intermediaries that could transfer their disaster risk. Results suggest that insurance stabilizes lender income and avoids credit contraction.

Keywords: natural disasters, microfinance, insurance, financial development, systemic risk, credit supply shocks, supervision and regulation

1. Introduction

This paper explores the consequences of natural disaster risk for financial intermediaries (FIs), particularly in the context of developing and emerging economies where financial markets are underdeveloped. We model a representative, dynamically optimizing lender managing a stock of equity capital to maximize divided payments to its shareholders. The model is calibrated using data from a Peruvian FI that specializes in microfinance and is vulnerable to the risk of severe El Niño, an event that brings torrential rains and flooding to northern Peru. The model demonstrates that loan losses from the event destroy the capital of the lender. Following the disaster, the lender reduces loan allocations, bringing them in line with a smaller capital base but also limiting access to credit for borrowing households and firms. Retained earnings allow the lender to recover after several periods, returning to pre-disaster levels of lending. Because of the business disruptions created by disaster losses, the risk of these events leads the lender to maintain capital reserves in excess of the amount required by the regulating supervisor. This strategy has the effect of reducing the supply of credit in non-disaster conditions and limiting profits and growth of the FI.

Additionally, we consider an insurance-like mechanism that would transfer the disaster risk of the FI. FIs in Peru can now purchase El Niño insurance, and we evaluate this mechanism in the model calibrated for the Peruvian microfinance intermediary. Results indicate that, when a severe El Niño occurs, insurance payouts

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offset capital losses. By protecting the lender’s equity capital, insurance prevents the credit contraction described above. As a result of managing its disaster risk with insurance, the lender maintains a lower capital ratio, increasing its loan allocations. Insurance against natural disasters seems to facilitate the lender’s objective of maximizing shareholder dividends. It also leads to the desirable public policy outcome of more consistent access to credit. Based on this research, a large microfinance intermediary in Peru has insured against El Niño for the past two years.

1.1. Background and literature review

A substantial body of theoretical and empirical research demonstrates that the financial system can play an important role in promoting economic growth (e.g., King and Levine, 1993). These benefits are seen across stages of development and firm size (Alfaro et al., 2004; Beck and Levine, 2004; Beck et al., 2008). For example, Fafchamps and Schündeln (2013) demonstrate that credit increases firm growth and firm entry and reduces the likelihood of firm exit in Morocco. Moreover, while microfinance will not solve the challenges of poverty and inequality, access to financial services for poor households and other underserved markets also seem to contribute to productivity and other socially desirable outcomes (Banerjee et al., 2009; Bauchet et al., 2011; Kaboski and Townsend, 2011). Thus, this paper is built on the premise that broad, accessible credit markets benefit communities and their economies and that increasing the resilience of these markets against systemic shocks is in the interest of both public and private stakeholders.

1.1.1. Capital reserves and systemic risk

In banking, capital is the value of the FI held by its long-term investors with subordinated claims. This capital is primarily shareholder equity; however, international banking standards identify several other forms such as long-term subordinated debt (Basel Committee on Banking Supervision, BCBS, 2011; 2006).

Capital is an important concept in the context of managing systemic risk as it identifies the losses an FI can sustain and remain solvent. Central to prudential banking standards are minimum capital requirements, a rule that the ratio of capital to risky investments such as loans cannot fall below a certain level (e.g., 8%). This rule has the effect of limiting the size of an FI based on its stock of capital. Unregulated or limitedly regulated FIs may face similar requirements from their liability holders. FIs operating with low capital ratios will tend to pay high borrowing rates or may be refused credit altogether. As a point of reference, 46% of FIs reporting to ?; an international database of FIs offering microfinance, are not regulated.

Capital is a binding constraint for many FIs in developing and emerging economies. Socially oriented investing has rapidly increased access to funds for FIs targeting under-served markets. For example, cross-border investments in financial inclusion grew from about $2 billion in 2005 to $25 billion in 2011 (Consultative Group to Assist the Poor, CGAP, 2012). Yet, these investors are primarily holding liabilities and only willing to invest equity in the largest, most secure FIs (MicroRate, 2011). To grow, FIs that cannot attract new capital must reinvest income in the firm.

Systemic credit risks are those events which create repayment problems for many borrowers concurrently, such as a macroeconomic crisis. Systemic events create loan losses that erode the capital of FIs. Peek and Rosengren (1995) use a static model to consider the response of an FI when its capital ratio falls below some minimal threshold. They demonstrate that as the capital constraint becomes binding, the FI must reduce the size of its assets and liabilities. In a dynamic context, FIs experiencing a low capital ratio will tend to originate fewer new loans. Reducing the level of loans originated reduces income, slowing recovery. This dynamic leads Van den Heuvel (2009) to conclude that: “The main cost of under-capitalization to the bank is thus that it must forgo profitable lending opportunities.”
1.1.2. Capital supervision and its opportunity cost

Prudential standards relying on capital requirements can create moral hazard, depending on how they are enforced. Calem and Rob (1999) describe a U-shaped pattern in risk taking where FIs operating close to the specified minimum capital requirements take less risk. Those operating with high capital ratios have incentives to increase risk taking which can improve returns as their excess capital insulates them from insolvency. FIs that are severely undercapitalized engage in the highest level of risk taking as the probability of insolvency is higher for these FIs so a high risk strategy may be the best possibility for recapitalizing.

This moral hazard motivates regulating supervisors to impose progressive penalties, increasing as the stock of FI capital falls farther below the minimum capital requirement. For example in the United States, supervisors impose “prompt corrective action,” a set of increasingly invasive responses to undercapitalization. FIs operating just below the minimum capital requirement are required, among other things, to provide a capital restoration plan and limit their asset growth. For significantly undercapitalized FIs, supervisors may also limit payments of dividends and management fees, dismiss directors and senior executives, and require the FI to divest from holdings in risky subsidiaries. For critically undercapitalized FIs, supervisors may also restrict payments on subordinated debt and place the FI under the management of another institution such as the Federal Deposit Insurance Corporation (United States Office of the Law Revision Counsel, 2013).

Given the threat of supervisory intervention, FIs often hold capital reserves in excess of minimum requirements. For example, Rime (2001) and Ediz et al. (1998) show that banks operating in Switzerland and the United Kingdom, respectively, actively managed their capital to remain above the regulated minimum. The amount held above the regulated minimum is related to the level of risk under which FIs operate. These findings imply that FIs are holding additional capital to minimizing the costly risk of supervisory intervention that may emerge from a systemic event. This strategy comes at the opportunity cost of reducing loan allocations and so reducing income.

1.1.3. Natural disasters as systemic shocks

International banking standards, including those for minimum capital requirements, focus on the role of large, international banks in the global economy. While these standards are written for the biggest banks in developed countries, they are often used to regulate a wide variety of FIs across diverse jurisdictions. For example, a survey of banking supervisors in 2010 indicated that 84% of jurisdictions had implemented or planned to implement Basel II, the contemporary version of international banking standards (133 jurisdictions completed the survey, Financial Stability Institute, 2010).

Because of their focus, these standards sometimes overlook important systemic risks affecting certain types of FIs and jurisdictions. We believe this is the case regarding natural disaster risks in the financial sectors of many developing and emerging economies. These economies are more vulnerable to disasters for a variety of reasons, including greater participation in vulnerable sectors such as agriculture and tourism, lower insurance penetration, less resilient public and private infrastructure, and more limited public safety nets.

Macroeconomic research generally suggests that severe natural disasters negatively affect growth in developing and emerging economies. Previous literature reports conflicting results, that disasters have negative (Rasmussen, 2004), positive (Skidmore and Toya, 2002), or neutral (Cavallo et al., 2010) effects on growth; however, recent studies use more detailed datasets to disaggregate effects and explain these results (Loayza et al., 2012; Noy, 2009; von Peter et al., 2012). For example, Loayza et al. (2012) demonstrate that economic sectors differ regarding the types of disasters to which they are vulnerable. Agricultural growth is more vulnerable to drought; industrial growth to flood. More generally, this literature identifies two offsetting effects of disasters on growth. First, disasters reduce the stock of productive capital and so reduce total output. Following neoclassical models, the marginal product of capital increases as its absolute level falls.
This dynamic leads to the second effect: reinvestment after the event stimulates the economy and generates higher returns. Noy (2009) notes that the net effect of a disaster is significantly affected by the ability of an economy to mobilize reinvestment. This capacity to mobilize investment is positively associated with the size of domestic credit markets, literacy rates, income per capita, openness to trade, government size, and institutional quality. Thus, recent research suggests that severe disasters tend to negatively affect growth because losses exceed a country’s reconstruction capacity (Hallegatte et al., 2007; Loayza et al., 2012; von Peter et al., 2012). This research also demonstrates that the negative consequences of disasters are greater in developing and emerging economies, likely because of 1) increased vulnerability as described above, and 2) a limited capacity to mobilize reinvestment.

Given the importance of FIs in allocating investments, a clearer understanding of the effects of disasters on these institutions is needed. Little is known about disaster-related credit risk, especially in developing and emerging economies. Following this logic, this paper demonstrates the significant challenges that disasters create for FIs and illustrates that these events affect vulnerable FIs in a fashion similar to other systemic risks. Natural disasters are spatially correlated events that affect many households and firms concurrently, leading to large loan losses. Thus, these events destroy the capital of FIs, and because of minimum capital requirements, lead to a credit contraction in the period following a severe event, slowing recovery for affected communities.

We illustrate these dynamics for an FI in Peru that specializes in microfinance and is vulnerable to severe El Niño events. El Niño creates catastrophic flooding in northern Peru (McPhaden, 2002). During the severe events of 1983 and 1998, rainfall was roughly 40 times normal levels for the months January to May (Skees and Murphy, 2009). This extreme weather leads to deaths and permanent injuries; destroys roads, bridges, homes, and businesses; inundates crops; and increases food prices, water-borne illnesses, and pests. Roughly 20% of the portfolio of this FI is in the vulnerable region. We participated in several development projects in Peru and collected data in collaboration with this FI during that field work.1

1.1.4. Insurance and disaster recovery

von Peter et al. (2012) also find that transferring risk to insurance markets may reduce the consequences of natural disasters. Their results suggest that it is only the uninsured portion of the loss that creates negative economic consequences. For well-insured events, the economic effect is neutral or even positive. These macroeconomic results motivate an examination of the underlying microeconomic mechanisms contributing to the value of insurance. We propose that this effect is partially explained by insurance reducing disruptions in the banking sector and so increasing the supply of credit after an event. Insured borrowers may be less likely to default after a severe event. By reducing loan losses, insurance preserves the capital of FIs. This capital can then be directed toward lending for reconstruction. We add insurance to the banking model in this paper and demonstrate that it protects lender capital and increases the supply of credit after the event.

In recent years, the development community has invested in a variety of projects to cultivate insurance markets in developing and emerging economies, including those to address natural disaster risk. These projects have tended to focus on insurance for households, especially the poor. While a variety of fascinating case studies have emerged, so have many challenges including limited demand and high transaction costs that threaten the viability of these markets (Murphy et al., 2011; Skees, 2008).

We took a different approach in Peru by using donor support to develop insurance products for FIs and other firms. For FIs, insuring against severe El Niño does not reduce the loan losses of its borrowers, but it offsets the resulting capital losses with an insurance payout. Thus, while the use of insurance by FIs would

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1 These projects were conducted by GlobalAgRisk, Inc. and were funded by USAID, the Bill & Melinda Gates Foundation, the United Nations Development Programme, and GIZ, a German development agency.
not directly address the disaster-related hardships of borrowing households and firms, it may prevent credit contractions that exacerbate disaster losses.

Some research also suggests that for managing disaster-related credit risk, insurance for FIs may be more effective than that for households. For example, Miranda and Gonzalez-Vega (2011) model a representative, dynamically optimizing microfinance borrower also using the case of a Peruvian microfinance market vulnerable to El Niño. Their results indicate that insurance purchased by individual borrowers is likely to increase credit risk by reducing their capacity to manage idiosyncratic risks. Evaluating the potential of subsidized insurance for individual borrowers, they note that the subsidies must be so large to improve borrower repayment that the cost likely outweighs the benefit. Finally, Miranda and Gonzalez-Vega examine a scenario in which the FI insures against its disaster exposure. Insurance slightly reduces the expected value but greatly reduces the volatility of the equity of the FI over the evaluation period.

After modeling the consequences of El Niño risk for the Peruvian microfinance intermediary, we evaluate the effects of El Niño insurance — whether the modeled lender chooses to insure and how insurance affects its performance. Unlike Miranda and Gonzalez-Vega (2011) who examine the case of a fully capitalized FI (i.e., one with a capital ratio of 100%), we consider a lender operating in the vicinity of its minimum capital requirement to evaluate the effects of capital constraints on the supply of credit in this risky environment.

1.2. Model

A representative lender operating in a competitive market attempts to maximize current and discounted future dividend payments to shareholders over an infinite horizon. This lender manages a stock of equity $k$, held by international investors, and is unable to attract additional equity investments. Lender income comprises three elements: revenues, expenses, and adjustments in asset values. Each period, the lender generates revenue by making loans $l$ at interest rate $r$. Lending is exposed to the production risks of borrowers, leading to an exogenous, random nonrepayment rate $\tilde{\xi} \in [0,1]$. Nonrepayment occurs due to idiosyncratic shocks as well as the realization of a natural disaster to which production is vulnerable. The lender borrows from international markets at rate $r^d$ and incurs origination costs associated with finding and evaluating borrowers. Because of the limited supply of good borrowers, this cost increases as the market grows, taking the form $\alpha l^2$. Finally, the lender adjusts its value based on loan losses $\tilde{\xi}l$. Thus, its income function is

$$\pi = r(1 - \tilde{\xi})l - r^d(l - k) - \alpha l^2 - \tilde{\xi}l.$$  

The regulating supervisor and equity and liability holders monitor the lender by its capital ratio $c$, which takes the form

$$c = \frac{k + \pi}{(1 - \tilde{\xi})l}.$$  

The lender is motivated to keep the ratio at a target level $\bar{c}$. If the lender’s capital ratio falls below this target, the regulating supervisor intervenes, restricting operations and implicitly sending a signal to liability holders of the lender’s risk. If the lender operates above the target, equity holders lose confidence in the lender and begin divesting. Thus, deviations from the target lead to the penalty $g(k, l) \equiv \beta (\bar{c} - c)^2 l$ such that deviations are punished at an increasing rate.

Lender income, penalties, and dividend payments affect lender equity, leading to the equity evolution equation

$$k' = (1 - \nu)k + \pi - g,$$  

where $\nu$ is the dividend rate. Given these conditions, we formulate the lender’s problem with the Bellman equation

$$V(k) = \max_{l \geq 0} \nu k + \delta E_\tilde{\xi}[V(k')]$$  

where $\delta$ is the lender’s discount rate.
1.2.1. Deterministic steady state

The model structure prevents describing its mechanics analytically; therefore, we solve the deterministic version of this model to demonstrate the lender’s behavior. Let $\bar{\xi} \equiv E[\tilde{\xi}]$. The Euler conditions are

$$V_l : \delta k^l V_{k^l} \leq \mu$$  (5)

$$l \geq 0, \mu \leq 0, l > 0 \implies \mu = 0$$  (6)

$$V_k : \nu + \delta k^k V_{k^l} = V_k.$$  (7)

Assuming an interior solution, (5) leads to the result that the lender originates loans until marginal revenue equals marginal cost

$$r(1 - \bar{\xi}) = r^d + 2\alpha l + \bar{\xi} + g_l.$$  (8)

This inverse supply function can be solved for $l$, leading to an optimal policy function $l^*(k)$. The supply of loans is increasing in the interest rate $r$ and decreasing in loan losses $\bar{\xi}$, borrowing costs $r^d$, and origination costs $\alpha$. At the steady state, economic profits equal zero so that

$$r(1 - \bar{\xi}) = \left[ r^d + (\nu - r^d) \frac{k^l}{k} \right] + \bar{\xi} + [\alpha l + \beta(\tilde{c} - c)^2].$$  (9)

Thus, the model adheres to the result from production theory that competitive markets lead marginal revenue to equal marginal cost and average cost. This result is shown in Figure 1 based on the model calibration described in the next section. Equation (9) also demonstrates that interest rates comprise three elements: 1) average financing costs for the lender, 2) loan losses, and 3) operational costs.

Figure 1: Deterministic solution

![Deterministic solution](image)

Note: The optimal level of lending in the deterministic model equates the marginal revenue, marginal cost, and average cost of lending.

1.2.2. Model with insurance

We additionally consider a case in which the lender can use an insurance-like mechanism to transfer its disaster risk. This insurance provides a payment based on an occurrence of the disaster, which is measured by indicator $t$. The lender can buy a sum insured $q \geq 0$ at premium rate $p$ and receive a payout based on the function $i(t)$. Thus, the insurance protects against the disaster event but does not directly reduce the loan losses of the lender. The lender’s new income function is

$$\pi = r(1 - \bar{\xi})l - r^d(l - k) - \alpha l^2 - pq - \bar{\xi}l + qi(t).$$  (10)
Table 1: Calibration summary

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Symbol</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lending interest rate</td>
<td>$r$</td>
<td>41.9%</td>
</tr>
<tr>
<td>Borrowing interest rate</td>
<td>$r^d$</td>
<td>5.5%</td>
</tr>
<tr>
<td>Origination expense</td>
<td>$\alpha$</td>
<td>0.0004</td>
</tr>
<tr>
<td>Capital penalty</td>
<td>$\beta$</td>
<td>25</td>
</tr>
<tr>
<td>Discount rate</td>
<td>$\delta$</td>
<td>0.94</td>
</tr>
<tr>
<td>Dividend rate</td>
<td>$\nu$</td>
<td>6.4%</td>
</tr>
<tr>
<td>Loan loss rate</td>
<td>$\tilde{\xi}$</td>
<td>{6.6%, 10.1%}</td>
</tr>
<tr>
<td>Capital requirement</td>
<td>$\bar{c}$</td>
<td>14%</td>
</tr>
<tr>
<td>Insurance payout</td>
<td>$i$</td>
<td>{0, 1}</td>
</tr>
<tr>
<td>Insurance trigger</td>
<td>$t$</td>
<td>24.5°</td>
</tr>
<tr>
<td>Insurance premium</td>
<td>$p$</td>
<td>8.05%</td>
</tr>
<tr>
<td>Disaster probability</td>
<td>$P[t \geq 24.5°]$</td>
<td>4.6%</td>
</tr>
</tbody>
</table>

Note: Brackets indicate values under non-disaster and disaster conditions, respectively.

2. Methods

This section describes model calibration and the numerical solution techniques used to solve the model. Mapping disaster severity to economic exposure is a non-trivial task. For example, Strobl (2012) models GDP losses from hurricanes using data on population and the wind speeds and paths of hurricanes. El Niño-related loan loss data from Peru are available for a single severe event and at the portfolio level, limiting opportunities to observe portfolio losses across events of different severities. Moreover, because the last severe event occurred more than 15 years prior to the current risk assessment, the capacity of historical losses to predict current exposure is greatly reduced. Given the paucity of data, we elicit the expert judgement of risk managers in the representative lender, using historical loss data as one reference point, to estimate the current exposure of this intermediary. Additionally, using current primitive financial parameters for the representative lender such as its lending and borrowing interest rates and origination expenses, we evaluate the financial and operational consequences of the estimated disaster-related loan losses. Table 1 summarizes calibration values.

2.1. Financial intermediary calibration

The representative lender is calibrated for one of several FIs with whom the authors collaborated in risk assessment and stress-test modeling. This FI specializes in microfinance with an average loan size of USD 1600. Its stated mission is to provide financial services to micro and small enterprises with the hope of improving quality of life for lower income people.

Data from the monthly income statement and balance sheet of the FI are available from the Peruvian banking regulator’s website.\(^2\) We calibrate financial performance parameters such as the effective annual lending interest rate (41.9%), borrowing interest rate (5.5%), and dividend rate (6.4%) using the average values from July 2009 to June 2012. During the evaluation period, the regulating supervisor required this type of FI to maintain a capital ratio of at least 14%, which we treat as the target capital ratio $\bar{c}$.

Origination expenses $\alpha$ result from a combination of administrative expenses, including investments in human resources, management information systems, research and development for new financial products, and geographic expansion. Identifying these expenses in the historic data is not possible; however, model stationary is a result of the convexity of origination expenses. We assume that the lender is operating in the vicinity of the mean of its steady state distribution of equity. Thus, by examining the level of equity held

\(^2\)\url{www.sbs.gob.pe}
by the FI, we can infer the approximate origination expenses that lead to this outcome. We scale the model by a factor of one over one million so that equity is roughly USD 80 (instead of USD 80 million), leading to an $\alpha$ of 0.0004.

The parameter $\beta$ on the capital penalty requires some logical constructs to calibrate. Deviating from the capital requirement may have direct financial implications (e.g., higher borrowing costs) and indirect ones (e.g., the supervisor dismissing board members). Both direct and indirect implications contribute to the value of $\beta$ for the representative lender, making it difficult to measure. We consider a desirable penalty calibration one in which the risk of the penalty affects lender behavior (e.g., holding capital in excess of the minimum requirement), yet the penalty is not so stringent that it leads the modeled lender to insolvency when shocks occur. A calibration of $\beta = 25$ meets these conditions. Finally, following Mendoza and Quadrini (2010), we set the discount rate $\delta$ at 0.94.

2.2. Risk survey and expected losses

The FI surveyed its office and credit risk managers regarding their perceived vulnerability of outstanding loans to severe El Niño. Twenty seven participants completed the survey from four vulnerable regions: Piura, Lambayeque, La Libertad, and Ancash. The survey included an open-ended question asking participants whether they are concerned about the risk of a severe El Niño. The expert responses offer a nuanced perspective on the diverse credit risks associated with these events:

- “If a similar event occurs as that in 1998, we would certainly have negative consequences for the entire economy, especially because the area we serve depends heavily on the viability of roads. These roads being blocked or interrupted by landslides would affect significantly the normal operations of our commerce and transport clients.”

- “We are concerned by severe El Niño. Our agency is in the Piura office and the city-level infrastructure is unable to prevent flooding because the main channel of the river runs through the city. Also, we have loans in grape production and other export products which are the main source of income for the rural area around the city, including an important source of income for dependent laborers. At the office in Unión, the river floods the farmland, as it has no proper outlet, and the rain affects agricultural products such as cotton, corn, and rice that provide the main income in the area.”

- “As the waters warm from El Niño, the aquatic species and fishing industry will move away from our coastline, leading to a shortage of fish.”

- “El Niño brings torrential rains that would cause serious harm to people, especially to the thousands of low income families living in mat huts.”

The survey respondents reported agriculture, commerce (i.e., firms in retail), transportation, and fishing as the most vulnerable sectors. Table 2 provides the average expected loan losses for each sector and region. Combining these estimates with its portfolio allocations indicates that the FI expects to lose 15% of the value of its loan portfolio in the vulnerable regions if a severe El Niño occurs. This type of FI anticipates to recoup about 60% of loan losses through exercising rights to collateral, implying that the expected default rate in the region for this event is 25%. Aggregating these results to the total portfolio, across all regions, the FI expects to lose 3.5% of the value of its outstanding loans from a severe El Niño event. This estimate is consistent with historical performance during the last severe El Niño of 1997–1998 and risk assessment results for other FIs in the region (Collier, 2010; Collier and Skees, 2012; Collier et al., 2011).
Table 2: Expected loan losses (%)

<table>
<thead>
<tr>
<th></th>
<th>Piura</th>
<th>Lambayeque</th>
<th>La Libertad</th>
<th>Ancash</th>
</tr>
</thead>
<tbody>
<tr>
<td>Agriculture</td>
<td>38</td>
<td>21</td>
<td>32</td>
<td>30</td>
</tr>
<tr>
<td>Commerce</td>
<td>26</td>
<td>10</td>
<td>15</td>
<td>33</td>
</tr>
<tr>
<td>Transport</td>
<td>18</td>
<td>3</td>
<td>22</td>
<td>16</td>
</tr>
<tr>
<td>Fishing</td>
<td>24</td>
<td></td>
<td></td>
<td>15</td>
</tr>
</tbody>
</table>

2.3. Probability of severe El Niño

Severe El Niño events are the result of a disruption in ocean and atmospheric circulation along the equatorial Pacific. This disruption increases the Pacific surface temperature, creating convection. As this warm, moist air moves west, it meets the cool air descending from the Andes in the east. The result is an extended period of torrential rainfall and flooding in northern Peru and southern Ecuador (Lagos et al., 2008). Because of this physical process, Pacific ocean temperatures are the key measure of El Niño used by climate scientists (e.g., see Wolter and Timlin, 1998) and the method we use to estimate the probability of El Niño.

Niño 1+2 is a measure of ocean temperatures near the coast of Peru and Ecuador collected by the National Oceanic and Atmospheric Administration (NOAA) of the United States. Khalil et al. (2007) find that rainfall in northern Peru is highly related to Niño 1+2. Ocean temperatures in this region follow an annual cycle. If El Niño emerges, flooding in northern Peru generally begins in February. Elevated ocean temperatures predate extreme rains. Our analyses suggest that average reported temperatures for Niño 1+2 for November and December are a strong predictor of impending torrential rains in northern Peru and so serve as the index by which we measure El Niño severity.

NOAA measures Niño 1+2 using a combination of data from ocean buoys, satellite sensors, and transocean liners. Data are available from 19503; however, the amount of buoys increased significantly in the 1970s and satellite readings were not available until the early 1980s. As a result, we use data from 1979 to 2012. Figure 2 shows the full time series and the data subset used in our probability estimations. Long-term historic data show multi-decade cycles in El Niño events; and significant debate exists in the scientific community on the effects of anthropogenic climate change on El Niño (Collins, 2005; McPhaden, 2002; Merryfield, 2006; van Oldenborgh et al., 2005; Yeh et al., 2009). Regarding our Niño 1+2 Index, no time trend is present in either series, and the augmented Dickey-Fuller test reports that neither the full time series (aDF=-4.19, p<0.01) nor the estimation subset (aDF=-4.21, p=0.01) has a unit root, an indication of stationarity.

Two severe El Niño events occur in the data series, in years 1982 and 1997. These elevated ocean temperatures in November and December correspond with flooding in northern Peru several months later, beginning in approximately February of 1983 and January of 1998, respectively. Both severe events caused significant damage, leading to many problems in the financial sector. Because the economy and financial system have changed so significantly since their occurrence, comparisons of the consequences of these two severe events are difficult. As a result, we treat severe El Niño as a binary outcome. Based on discussions with climate scientists and reports on what ocean temperatures lead to significant losses in Peru, we define a temperature \( t \) exceeding 24.5\(^{\circ}\) on the Niño 1+2 Index as a severe El Niño event.

We assess the probability of severe El Niño using maximum likelihood estimation (MLE) of the generalized extreme value (GEV) distribution. This distribution is commonly used for estimating infrequent events with limited data due to its flexibility as its parameters allow it to approximate a variety of long-tailed distributions. It is derived from an assumption of the data’s asymptotic convergence, namely it is the

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3 [http://www.cpc.ncep.noaa.gov/data/indices/ersst3b.nino.mth.81-10.ascii](http://www.cpc.ncep.noaa.gov/data/indices/ersst3b.nino.mth.81-10.ascii)
limiting distribution of the maxima of $N$ independently and identically distributed, random variables drawn from a distribution as $N \to \infty$ (Cameron and Trivedi, 2005). The cumulative distribution function for the GEV distribution is

$$G(x; \mu, \sigma, \kappa) = \exp \left\{ - \left[ 1 + \frac{\kappa(x - \mu)}{\sigma} \right]^{-1/\kappa} \right\}$$

(11)

where $\mu$, $\sigma$, and $\kappa$ parameterize the location, scale, and shape of the distribution, respectively (Jenkinson, 1955). The GEV distribution has three types, which depend on the value of $\kappa$. Type 1, the Gumbel distribution, occurs when $\kappa = 0$ and is the most familiar for many economists as the logit model is derived from it (Cameron and Trivedi, 2005). Its tail decreases exponentially, similar to the normal distribution. Type II, the Fréchet distribution, occurs when $\kappa > 0$ and is similar to Student’s $t$, Pareto, and Cauchy distributions whose tails decrease more gradually. Type III, the reverse Weibull distribution, occurs when $\kappa < 0$ and is marked by relatively short tails, similar to the beta distribution (Woo, 1999).

Smith (1985) demonstrates that the GEV distribution can be estimated using MLE, showing that the typical asymptotic properties of MLE estimators hold if $\kappa \geq -0.5$. The results of our MLE using the Niño 1+2 index for years 1979 to 2012 provide GEV distribution parameters of $\mu = 21.861$, $\sigma = 0.809$, and $\kappa = 0.041$, indicating that Fréchet is the best fitting distribution for this index. Figure 3 provides a histogram of the index values and the estimated probability density function. Based on this analysis, the annual probability of severe El Niño is

$$P[t \geq 24.5^\circ] = 1 - G(24.5^\circ) = 4.6\%.$$  (12)

2.4. El Niño insurance

A parametric insurance product is now sold in Peru to address the adverse consequences of event-related flooding. That contract uses the Niño 1+2 Index as the sole basis of payments. Because the Niño 1+2 Index
measurements predate Niño-related flooding in northern Peru, El Niño insurance has the potential to make payments before disaster losses emerge. Thus, it is likely the first regulated forecast insurance in the world (Collier and Skees, 2012).

Following our treatment of El Niño as a binary event, we use a simplified insurance contract structure in this paper such that the full sum insured is paid if severe El Niño occurs

\[ i(t) = \begin{cases} 1 & \text{if } t \geq 24.5^\circ \\ 0 & \text{o.w.} \end{cases} \] (13)

From discussions with insurers and reinsurers, we estimate that for this risk the loads for commissions, administration costs, etc., would be approximately 75% of the actuarially fair rate, resulting in an annual premium rate of about 8.05% of the sum insured for this stylized contract.\(^4\)

### 2.5. Solution techniques

The Bellman equation (4) is solved using the method of collocation (Judd, 1998; Miranda and Fackler, 2002). The collocation method calls for the value function \( V(k) \) to be approximated using a linear combination of \( n \) known basis functions \( \phi_j \):

\[ V(k) \approx \sum_{j=1}^{n} z_j \phi_j(k). \] (14)

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\(^4\)We would like to thank Grant Cavanaugh for his contributions to estimating the probability of El Niño. For an in-depth analysis on this topic, please see Cavanaugh (2013). Additionally, insurers in Peru offer a linearly increasing payout structure. For example, one contract has a trigger of 24° and exhaustion point at 27°, where the full sum insured is paid. As a result, the probability estimates developed here do not apply to those contracts.
The unknown coefficients $z_j$ are then fixed by requiring the value function approximants to satisfy the Bellman equation (4), not at all equity levels $k$, but rather at $n$ judiciously chosen collocation nodes $k_j$. The collocation method replaces the Bellman functional equations with a set of $n$ nonlinear equations with $n$ unknowns that are solved using Newton’s method. The collocation method can generate highly accurate approximate solutions to the Bellman equation, provided the basis functions and collocation nodes are chosen judiciously and their number $n$ is set adequately high. We chose Chebychev polynomials and equally-spaced nodes to compute the approximate solutions for the Bellman equations. The solution was computed using the CompEcon 2012 Toolbox routine *dpsolve* (Miranda and Fackler, 2002).

3. Results

This section describes the optimal behavior of the lender and simulates the effects of a natural disaster on its operations. We also compare results in which the lender retains its disaster risk with those in which the lender transfers it using insurance.

3.1. Lender simulation, retaining risk

Figure 4 illustrates results for the model in which the lender retains its risk, the model without insurance. In the figure, each period represents a year, and the disaster occurs in Period 0. The figure shows that because of risk, the lender sets loan allocations so that it operates with a buffer above minimum capital requirements. This result is consistent with the behavior of the FI, which during the evaluation period, maintained an average capital ratio of 16.8%.

The disaster creates loan losses that lead to income losses. Income losses reduce the capital of the lender and push its capital ratio below the minimum requirements. Given this smaller equity base, the capital requirement motivates the lender to realign its balance sheet by originating fewer loans, disrupting the provision of credit in the market.

Recovery occurs as the lender retains earnings during the periods following the disaster. Facilitating this recovery is the ready supply of good borrowers created by the credit contraction, leading to lower origination expenses and so higher income. These results indicate that loan origination returns to pre-disaster levels after approximately four to five years, which is consistent with the expected recovery period communicated by credit risk managers in FIs in Peru.

3.2. Capital constraints and the 1998 El Niño

These results motivate the question: did the 1998 El Niño create the capital problems demonstrated in the simulation results? While the microfinance institution for which the model is calibrated was not operating during that event, we examine the performance of other FIs in the region. Figure 5 shows the ratio of equity to loans, approximately the capital ratio, for three FIs operating in the region during 1998. Those FIs are owned by local municipalities and provide credit to households and firms of a variety of sizes.

This time series illustrates a common pattern that FIs in newly developed credit markets often operate with large capital reserves but reduce these reserves as markets grow. Lenders in nascent markets are managing a great deal of risk, such as lending to borrowers with no previous credit history and developing and testing underwriting procedures. These lenders are also building a clientele large enough to meet its lending capacity. As markets mature, the capital ratios of FIs converge toward minimum requirements.

During this maturation process in northern Peru, El Niño occurred. The shaded area in Figure 5 is a four year period beginning with the approximate onset of the El Niño event in January 1998 and ending in December 2001. The months during and after the El Niño event represent a period of high volatility in the capital ratios of each FI; however, the figure does not mimic the plummet and recovery of the capital ratio shown in Figure 4. Because these FIs were not operating near the minimum capital requirements, their
operations were not constrained by capital losses. Instead, Collier and Skees (2012) report that these FIs used their excess capital to increase lending to improve their performance indicators following the disaster. For example, portfolio at risk (PAR) is an indicator describing the proportion of the portfolio on which loan payments are a certain number of days (e.g., 90) overdue. Assuming an FI can identify creditworthy borrowers, a dramatic increase in lending following a disaster would reduce PAR.

While the excess capital reserves held by these FIs in 1998 minimized the potential disruptions of El Niño on their operations, their reserves are now much closer to the minimum requirements. Thus, these FIs are no longer in a position to rely on a strategy of growing to recover from a severe event.

### 3.3. Lender simulation, transferring risk

Figure 6 illustrates results for the model in which the lender transfers its risk. The lender chooses to insure a portion of its disaster exposure. With this protection, the lender reduces the buffer it holds above minimum requirements, increasing its loan allocation. When the disaster occurs, the insurance payout offsets loan losses and so smooths lender income, protecting its equity and maintaining the stability of the capital
Figure 5: Financial intermediary capital ratios and the 1998 El Niño

Note: During the severe El Niño of 1998, financial intermediaries held large capital reserve; now they do not, increasing their vulnerability.

ratio. This protection not only allows the lender to avoid the adverse consequences of operating below the capital requirement, but also stabilizes dividend payments to shareholders. Perhaps most importantly from a social perspective, the insurance prevents the contraction of credit during the period following the disaster.

Examination of the optimal sum insured indicates that it is set at a point that smooths the capital penalty across disaster and non-disaster states of the world. Figure 7 illustrates that insurance is chosen to match the potential penalty that the lender would pay if the disaster occurred. Other common uses of insurance are income and asset protection. This figure also shows for each period the loan losses the lender would incur during a disaster and the normal (non-disaster) income the lender can expect, illustrating that income and asset risk are not driving insurance purchase. Instead, the lender is minimizing the cost of the event by managing its capital ratio to avoid falling below minimum capital requirements.

An important public policy question pertains to the effect of insuring on access to credit more generally — does the cost of insuring reduce the supply of credit in periods preceding the disaster? The insured lender is more leveraged than its uninsured counterpart (i.e., its capital ratio is lower in periods preceding the disaster), and the additional revenue generated from this leveraging at least partially offsets the cost of insuring. For this model’s calibration, the difference in origination between the insured and uninsured lender in the period before the disaster is less than one percent, a difference within the margin of modeling error. Thus, we conclude that insuring does not reduce the supply of credit during non-disaster periods.

4. Discussion

This research demonstrates that natural disasters can be systemic risks that significantly challenge FIs in vulnerable regions. These risks are likely to be more severe in developing and emerging economies and therefore deserve special attention in those jurisdictions. Because FIs are instrumental to mobilizing investment after a disaster, increasing their resilience may substantially affect the development of vulnerable economies.
A rich literature on managing systemic shocks in the financial sector exists, much of which can be applied to disaster risk.

Managing disaster risks is in the interest of FIs as these events disrupt income and dividend payments. Based on this research, a highly regarded FI in Peru that specializes in microfinance purchased El Niño insurance in 2011 and 2012. That FI reports that the insurance not only reduces its current vulnerability, but that it plans to use the insurance to increase financial inclusion in the vulnerable region. By reducing risk and stabilizing financial performance, insurance may also increase the willingness of investors to hold equity and other forms of capital in FIs operating in vulnerable regions.

Because of the many potential externalities in banking, systemic risk management relies heavily on public supervision and market discipline. Monitoring and encouraging FIs to proactively manage disaster risk is in the interest of supervisors, credit rating agencies, and investors in vulnerable regions. Regarding public interests, these events have the potential to disrupt the provision of credit, potentially exacerbating the consequences of natural disasters. While not explicitly modeled here, systemic events can also threaten the
Note: The modeled lender insures to avoid regulatory penalties resulting from capital losses that would occur with an El Niño.

claims of depositors and other liability holders and lead to contagion in the financial sector. International standards require tailoring to allow for risk-based supervision of disaster exposures. Credit rating agencies and some investors employ rating methodologies that face many of the same limitations as international banking standards, emphasizing risks to large banks in developed economies, and so also require tailoring (Collier and Skees, 2012).

This research suggests that along with improving monitoring of disaster risks, encouraging risk management through mechanisms such as insurance provides both public and private benefits. For example, tailoring standards so that FIIs could manage disaster risk concentrations using additional capital reserves, purchasing financial risk-transfer, and/or investing in diversification would allow FIIs to minimize the cost of managing this risk. These cost savings would eventually translate to lower interest rates for borrowing households and firms.

One limitation of this research is that this model evaluates disaster risk in isolation of other systemic risks such as business cycles, currency fluctuations, commodity price shocks, etc. The variety of risks facing FIIs motivate comprehensive risk management strategies that include layering financial mechanisms. Capital reserves are ubiquitous, flexible, important mechanism for managing small systemic shocks. For the risks of greatest existential concern to the FI, insurance represents an attractive alternative. Thus, the results of this research are most relevant for FIIs worried about a specific natural disaster risk; for FIIs exposed to many large systemic risks, its results overstate the benefits of insuring.

A second limitation is specific to index insurance, the risk transfer mechanism modeled here. While the core results of this research are generalizable to many types of insurance, index insurance tends to be more vulnerable to basis risk than is traditional insurance. Basis risk describes the possibility of a discrepancy between the severity of the disaster as experienced by the FI and that as measured by the index used for payouts. Basis risk is not explicitly modeled in this research. A risk management strategy that uses a combination of risk transfer, reserves, and other mechanisms is well suited to manage basis risk as capital reserves can be used to address the basis. Because index insurance substantially reduces moral hazard and adverse selection and so can be provided at a lower cost, it may be a more attractive mechanism to FIIs than
traditional insurance despite basis risk.

These findings offer many potential extensions through future research. Of primary interest is empirical research testing the modeled results. That research requires data on FIs operating in the vicinity of their minimum capital requirements that experience a natural disaster. Another important extension would be evaluating the consequences of disaster risk on foreign direct investment in vulnerable sectors, such as agriculture, and testing the potential of insurance mechanisms to add value in this context.

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