Credit Access and Severe Climate Risks: Implications of Information and Geography for Lending in Vulnerable Communities

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Abstract
This paper contributes a theory for understanding the challenges of severe climate risks for local credit markets, positing that disaster vulnerability is an inherent consequence of the pervasive credit market structure used to serve micro, small, and medium enterprises (MSMEs), especially in developing and emerging economies. It predicts that disaster risks reduce the average credit supply and increase its volatility. These predictions are supported by evidence from a dynamic model of lender behavior under risk and analyses of post-disaster lending from a panel of MSME lenders. The panel results indicate that disasters significantly and meaningfully reduce lending and are largely explained by capital constraints following these events. Finally, the paper discusses and models disaster-contingent claims as a means to strengthen community credit markets using the example of a recently developed El Niño insurance market in Peru.

1. Introduction

This paper provides a theory regarding how local credit markets function under severe climate risks with an emphasis on credit for micro, small, and medium enterprises (MSMEs), the economic foundation of many communities. Its key insight is that the strategies frequently adopted by lenders to serve MSMEs also increase their vulnerability to disasters. Specifically, previous evidence suggests that to overcome asymmetric information, these lenders specialize geographically to select and monitor borrowers (Agarwal and Hauswald, 2010; Petersen and Rajan, 2002) and that lending to opaque borrowers creates opaque lenders and so reduces access to capital markets (Diamond, 1984; Houston et al., 1997; Portes and Rey, 2005; Stein, 1997). The theory predicts that capital constraints and an inability to reduce portfolio concentrations of spatially-correlated disaster risk motivate lenders in vulnerable communities to 1) reduce their supply of credit, and 2) further contract credit after a severe event.

Theoretical and empirical evidence support these hypotheses. I develop a dynamic, partial equilibrium model to examine lender behavior under risk. A substantial body of research identifies asymmetric information as a primary driver for the industrial organization of MSME credit markets as discussed below. I treat this market structure as given, not modeling the informational asymmetries directly, but taking as stylized facts that they lead to convex selection and monitoring.
costs and limit access to external capital. The model is calibrated for an MSME lender in Peru that is vulnerable to El Niño, an event that brings torrential rains and flooding. This lender conducted a risk assessment survey among its field office and credit risk managers. The modeled lender manages a stock of equity and disasters create loan losses that lowers this capital stock. In response, the lender contracts credit, reducing loan allocations to bring them in line with a smaller capital base. The risk of these shocks motivates the lender to maintain a capital buffer above minimum requirements, which has the effect of reducing the credit supply in non-disaster conditions. These results are consistent with the experience of communities in Peru affected by the severe El Niño of 1998.

The paper also provides the first broad-scale empirical analysis of credit provision following natural disasters using a panel of MSME lenders in developing and emerging economies (MIX Market, 2014). I use a first-difference model with 1,321 lender-year observations from 58 countries and show that these MSME lenders lend less following disasters. On average, disasters in the top quartile reduce loan growth by 11 percentage points in the current year and another 8 percentage points the following year (median annual loan growth in the sample is 24%). Reductions in credit growth following disasters seem to be largely explained by capital constraints. MSME lenders with low capital ratios before a disaster lent substantially less afterward; however, lenders with high capital ratios lent at the same rate following the event.

Finally, the paper discusses disaster-contingent claims as one means to strengthen community credit markets. While a variety of private strategies and public interventions may reduce the vulnerability of local lenders, many are challenged by the same information problems that limit access to credit for MSMEs (e.g., see Just et al., 1999; Kunreuther and Pauly, 2006; Levitsky, 1997). Parametric-based contingent claims are a relatively new approach that is less prone to asymmetric information. These mechanisms allow lenders to transfer their (unobserved) portfolio concentrations of disaster risk to a counterpart (e.g., a reinsurer) by contracting based on an index of the disaster that is observable to both parties. I model El Niño insurance, a parametric insurance product available for purchase by financial intermediaries in Peru. The results demonstrate that disaster-contingent claims can greatly reduce credit supply shocks and expand access to credit in vulnerable communities.

1.1. Motivation and theory

Severe climate and other natural disaster risks are increasing due to a confluence of more volatile weather, taxed natural resources, and development and urbanization (Kunreuther and Michel-Kerjan, 2009; Samson et al., 2011; Stern, 2008). Natural disasters have caused an USD 2.11 trillion in economic losses and 760,000 fatalities in the last decade (2004–2013, Aon Benfield, 2015). The latest Intergovernmental Panel on Climate Change (IPCC, 2013) report cites increasing evidence that extreme events including heat waves, severe rainfall, drought, and tropical cyclones are all expected to increase by the late 21st century; moreover, current temperature and rainfall extremes have already increased relative to 1950. Urbanization exacerbates the problem of more frequent, extreme events (Stern, 2008), and the UN Department of Economic and Social Affairs (2014) predicts that two thirds of the world’s population will live in urban settings by 2050 (compared
to one third in 1950). Much of this evolution will occur through migration from rural areas to small and medium communities. Consequently, the World Economic Forum’s 2014 survey reports the perceptions of 900 public and private sector world leaders that extreme weather events are one of the risks of concern most likely to occur (second most likely after interstate conflict World Economic Forum, 2015). Consequently, the World Economic Forum’s 2014 survey of 900 public and private sector world leaders finds extreme weather events as one of the most frequently cited risks of concern and one of the risks most likely to occur (second only to interstate conflict, World Economic Forum, 2015).

Macroeconomic evidence suggests a consequential role for financial intermediation in mitigating the adverse economic consequences of natural disasters (Hallegatte et al., 2007; Loayza et al., 2012; Noy, 2009; Skidmore and Toya, 2002; von Peter et al., 2012). Disasters cause systemic losses that tend to increase demand for investment – as the absolute level of physical capital falls its marginal product rises. Among other factors, Noy (2009) finds that recovery is positively influenced by the size of local credit markets but unaffected by stock markets, suggesting that financing for households and MSMEs may be particularly important for facilitating recovery.

MSMEs contribute substantially to the economies of developing countries and remain one of the most difficult credit market segments for lenders to reach. Formal SMEs account for approximately 45% of the manufacturing labor force and 30% of GDP in developing countries (and much more if accounting for the informal economy, Ayyagari et al., 2007). In these countries, barriers have delayed the implementation of technological advancements that have reduced credit constraints in developed countries. About 50% of MSMEs in developing countries identify access to financial services as an operational constraint, and 40% report not having any access to credit from a financial institution. This developing country market gap is over USD 2 trillion (Stein et al., 2013).

Dell et al. (2014) offer an excellent overview of research on weather and economic outcomes related to labor, industrial, and agricultural productivity and identify the need for a deeper understanding of the mechanisms linking the weather and economy. Academic research on credit markets and severe climate risks remains nascent so I borrow from the MSME and financial intermediation literatures, proposing a theory based on four well-documented findings: 1) MSMEs tend to be informationally opaque and vulnerable to significant risk; 2) lending to MSMEs motivates financial intermediaries (FIs) to specialize geographically; 3) lending to MSMEs increases capital market frictions for FIs; and 4) the challenge of supervising MSME lenders motivates a strong reliance on minimum capital requirements.

My theory states that MSME lenders frequently operate under a combination of capital constraints and portfolio concentrations of disaster risk. I test two hypotheses regarding lender behavior that have important implications for vulnerable communities:

**Hypothesis 1 (Risk Hypothesis).** Disaster risk reduces the supply of credit by local lenders.

**Hypothesis 2 (Response Hypothesis).** These lenders lend less following disasters due to capital constraints.

Disaster risk seems to be a first-order problem for many communities around the world, as discussed below; however, the hypotheses could be applied more generally to other credit risks against which
community lenders may be unable to diversify. If confirmed, Hypothesis 1 implies that in the long run, disaster risk increases the amount of capital needed to meet credit demand in vulnerable communities (and consequently increases the cost of credit). In the short run, confirmation of Hypothesis 1 suggests a reduction in overall credit provision in communities where these markets are underdeveloped and so would contribute to the explanation of current credit market gaps.

2. Literature review

This section provides an overview of the research findings on which the theory in this paper is based and informs the theoretical and econometric sections to follow.

2.1. Micro, small, and medium enterprises; risk; and asymmetric information

MSME operations are highly risky due to a variety of internal and external factors (Everett and Watson, 1998; Headl, 2003; Pompe and Bilderbeek, 2005; Wiklund et al., 2010). Research on risk and MSMEs has frequently fallen into three relevant segments: small and medium enterprises (SMEs), agricultural producers, and microenterprises of the poor. Agricultural vulnerability to climatic risk is clear. SMEs tend to be at greater risk than larger firms because they are often more specialized and spatially concentrated and have fewer financial resources (Tierney, 1997; Wasileski et al., 2011). Despite strong social safety nets in the U.S., its Small Business Administration (2013) reports that 25% of firms permanently fail following a major disaster. The poor are the least equipped as they often live and work on marginalized land and manage risk through informal, communal arrangements that break down during extreme events (Fafchamps and Lund, 2003; Stern, 2008; Townsend, 1994).

Despite advances in informational and financial technologies that have increased hard, quantifiable data on MSMEs (Berger and Udell, 2006; DeYoung et al., 2004; Petersen and Rajan, 2002), lending constraints due to opacity often remain high, especially in developing and emerging economies for agricultural producers (Binswanger and Rosenzweig, 1986; Boucher et al., 2008; Hoff and Stiglitz, 1990), SMEs (Agarwal and Hauswald, 2010; Beck et al., 2008; DeYoung et al., 2004; Petersen and Rajan, 2002), and the poor (Armendáriz and Morduch, 2011; Behr et al., 2011).

Frequently, serving these markets motivates lenders to specialize geographically (Basel Committee on Banking Supervision, BCBS, 2010; Binswanger and Rosenzweig, 1986; DeYoung et al., 2004; Petersen and Rajan, 2002; Stein, 2002). For example, Agarwal and Hauswald (2010) find that distance challenges the ability of lenders to monitor SMEs, increasing lending costs, so that proximity to lenders increases credit access and lowers interest rates. Small, local banks seem to have a comparative advantage for collecting soft information (Berger and Black, 2011; Berger et al., 2005; Petersen and Rajan, 2002). Agricultural lenders hire agronomists and place offices near producers to facilitate monitoring (Wenner et al., 2007). Community banks and many microfinance intermediaries engage in long-term relationships with clients, capitalizing on local knowledge, interacting frequently with borrowers, and often improving loan terms for proven clients (Agarwal and Hauswald, 2010; Armendáriz and Morduch, 2011; Behr et al., 2011; Uchida et al., 2012).
2.2. Capital market frictions and opacity

Access to external capital markets is constrained for lenders relying on soft information because they have internalized the information problem of their borrowers and so are managing portfolios of assets that are difficult to value (Diamond, 1984; Houston et al., 1997). SME lending has been the archetype of information-based capital market frictions (see Stein, 2002). Portes and Rey (2005) find empirical support that informational barriers help explain frictions in international financial markets. These information problems motivate investors to fund FIs with fixed income liabilities (Diamond, 1984).

As one example, capital market frictions and strong preferences for debt investments are ongoing themes of the socially oriented sector known as “impact investing,” which invests heavily in expanding underdeveloped credit markets (Consultative Group to Assist the Poor, CGAP, 2012; MicroRate, 2011). This sector’s cross-border investments in MSME lenders has grown from about USD 2 billion in 2005 to USD 25 billion in 2011 (CGAP, 2012). While access to equity capital is frequently cited as a capacity constraint for MSME lenders, only about 20% of these investments are in equity and those are in the largest, most secure MSME lenders (MicroRate, 2011; Symbiotics, 2013).

2.3. Supervision under opacity

Regulatory supervision is also constrained by asymmetric information (e.g., see Boot and Thakor, 1993; Tirole, 1986). Almost without exception, MSME lenders determine their regulatory capital based on the simplest approaches in the Basel Accords, banking regulation guidelines provided by the Bank for International Settlements (BCBS, 2006, 2010, 2011). In this context, regulatory capital is not a reflection of portfolio risk, but an observable indicator of loss capacity. Moreover, lenders tend to increase risk taking as the capital ratio approaches zero because highly risky bets become the greatest possibility for recovery (Calem and Rob, 1999). This moral hazard motivates regulating supervisors to intervene proactively via “prompt corrective action,” a set of increasingly invasive responses to undercapitalization (e.g., in the U.S., moving from the development of a capital restoration plan to limiting risky investments to putting the FI in receivership as capital falls to critical levels, The U. S. Office of the Law Revision Counsel, 2013). Prompt corrective action has been shown to motivate FIs to both increase capital reserves and reduce portfolio risk (Aggarwal and Jacques, 2001). FIs choose capital reserves that minimize the risk of costly supervisory intervention that may emerge from a systemic event. Rime (2001) and Ediz et al. (1998) show that banks operating in Switzerland and the United Kingdom, respectively, actively managed their capital to avoid falling below the regulated minimum.

Capital market frictions and capital regulation have been shown to interact to reduce credit supply in economic downturns. For example, Peek and Rosengren (1995) find the interaction of

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1 Ninety six percent of jurisdictions (n=143) responding to the World Bank’s Banking Regulation and Supervision Survey reported that they were using either Basel I or II, the international regulatory standards developed by the Bank for International Settlements at the end of 2010 (World Bank, 2011). For example in Peru, deposit-taking SME lenders and microfinance intermediaries are managed with standards from the Accords (e.g., Superintendencia de Banca, Seguros, y AFP, SBS, 2009). Greenspan (1998) notes that these approaches do not encourage diversification, hedging, or other portfolio risk mitigating approaches.
an economic downturn and regulation focused on minimum capital requirements led banks in New England to shrink in the early 1990s to bring their holdings in line with a smaller capital base. Also, Gambacorta and Mistrulli (2004) find that lenders with lower capital ratios lent less following reductions in GDP growth in Italy between 1992 and 2001.

2.4. Bank holding companies and internal capital markets, a contrasting case

Bank holding companies represent a contrast to opaque, geographically concentrated MSME lenders as they have the capacity to manage local bank distress with internal capital markets (Ashcraft and Campello, 2007; De Haas and Van Lelyveld, 2010; Stein, 1997). Large banks have been shown to use internal capital markets inter-regionally in the U.S. (Campello, 2002; Houston et al., 1997) and across international jurisdictions (De Lis and Herrero, 2010). These internal markets insulate subsidiaries from shocks, allowing them to maintain lending during a crisis as local lenders contract credit.

Moreover, Stein (2002) suggests a causal interplay between information, organization, and internal capital markets. Effective internal capital markets are only likely to function for transparent subsidiaries because their hard information can be communicated across the hierarchy. For opaque subsidiaries, the parent cannot distinguish between bad luck and bad management and so are less likely to reallocate capital to poor performers. Thus, even if their lender is a subsidiary in a bank holding company, opaque MSMEs may experience credit supply constraints when more transparent markets operating in close proximity do not.

2.5. Previous research on natural disasters and credit dynamics

The pattern of lenders avoiding or rationing credit in communities and sectors that are highly vulnerable to disasters is documented well (e.g., see Binswanger and Rosenzweig, 1986; Boucher et al., 2008; Hoff and Stiglitz, 1990). Only a handful of papers examine the consequences of a natural disaster on credit markets. Most research thus far has focused on demand for credit after a disaster and is consistent with the theory presented above, that disasters 1) generally increase demand for credit, and 2) seem to exacerbate information problems for firms without a previously established lending relationship.

The Federal Reserve Bank of New York (2014) examine disaster-related credit demand in one of the most developed markets in the world. One third of firms in government-declared disaster counties were negatively affected by Hurricane Sandy in a survey of roughly 1,000 small firms in Connecticut, New Jersey, and New York. Those affected firms reported greater financing needs than unaffected firms, and 40% increased their debt due to Sandy.

Del Ninno et al. (2003) highlight increased demand for consumption credit for households experiencing the major 1998 flood in Bangladesh. They find increased incidence of borrowing across all levels of household wealth. Moreover, increased borrowing is seen not only among households experiencing direct losses from the flood (e.g., inundated assets), but also those not directly affected, seemingly due to higher food prices and reduced income resulting from labor market disruptions.

Berg and Schrader (2012) study the effects of volcanic eruptions on credit access for MSMEs in Ecuador using loan application data for a multinational, socially oriented MSME lender. Credit
applications increased following volcanic activity. While approval rates were unaffected for previous borrowers, new applicants were significantly less likely to be approved after a volcanic event.

While increased demand for credit after a disaster would theoretically increase interest rates, the limited available empirical evidence suggests that this does not occur (e.g., Berg and Schrader, 2009). I also find no evidence of increasing interest rates in MSME markets in Peru following the 1998 El Niño (discussed in Appendix A). Unchanging interest rates could be explained in several ways including strategies to overcome asymmetric information as identified by Stiglitz and Weiss (1981), self interest (protecting the viability of borrowers, Berg and Schrader, 2009), public relations (avoiding the appearance of price gouging), or regulatory restrictions (requirements that interest rates follow the reported schedule of an FI).

Taken as a whole, these results of unaddressed demand and sticky interest rates suggest that changes in credit market outcomes following disasters are driven by the quantity of credit supplied. While some studies have documented supply constraints of natural disasters, in almost every case, its treatment has been cursory and ancillary to the core research objectives. Hosono et al. (2012) study SME investment following the Kobe earthquake in 1995, finding evidence that firm production was adversely affected by credit supply constraints. For firms outside the earthquake-affected area, those whose lenders were in the affected area invested less than SMEs whose lenders were outside the affected area. Also, firms in damaged areas generally invested more after the event.

Superficial evidence from developing and emerging markets also identifies adverse effects of disasters on lenders. Caprio and Klingebiel (1996) cite drought as a precipitant of banking crises in Kenya (where eight FIs and one mortgage lender were liquidated from 1986-1989) and Senegal (where six FIs were liquidated and three were restructured and recapitalized from 1988-1991). Dowla (2011) reports that Grameen Bank, with 25% of its borrowers in default, required a government bailout to recover from the severe floods of 1987 in Bangladesh. Siamwalla et al. (1990) notes that, following droughts in Thailand, formal and informal rural lenders were ailing and unable to meet credit demand for consumption loans, and affected borrowers were unable to obtain credit from other FIs.

The model presented in this paper has some similarities with Collier and Skees (2012) who provide a banking simulation model to estimate the consequences of severe El Niño for vulnerable microfinance intermediaries. They use an Excel-based, risk-planning educational tool for lenders that does not identify optimal lender behavior, the purpose of the model presented here.

3. Theoretical model

This section develops a dynamic, rational expectations, partial equilibrium model to examine lender behavior under disaster risk. The model takes three stylized facts from previous research on MSME lenders as given. First, lenders overcome asymmetric information through close monitoring and selection of borrowers. The cost of this information is convex as the lender expands. Second, lenders hold undiversifiable portfolio concentrations of spatially correlated risk. Third, lender opacity limits or even precludes access to external equity markets. Before discussing the model, I review several underlying assumptions.
Long-run behavior in a static economy. The lenders studied in the empirical sections of this paper are frequently serving underdeveloped credit markets and growing quickly. I model lender behavior in the long run, holding implied local economic conditions and interest rates constant and examining the lender’s steady-state distribution and deviations from it. This approach has several advantages for isolating the effects of disasters, but warrants caution as long-run conditions may differ from current ones.

Disaster risk is meaningful. The model intends to capture lending in communities where severe climate or other natural disaster risk is a first-order problem. The case from Peru discussed in Section 4 shows that portfolio concentrations that seem relatively small (e.g., an expected loss of 3.5% of the portfolio due to a severe flood) have large operational implications. Moreover, Section 5 provides evidence that meaningful disaster vulnerability is widespread among MSME lenders in developing and emerging economies.

One period loans. I assume that the investment portfolio can be rebalanced every period to facilitate the analysis. Modeling multi-period lending would only strengthen the argument regarding the shortage of new credit following a disaster.

Non-monetary regulatory penalties. The model describes a regulated lender that must adhere to minimum capital requirements, which is consistent with the Peruvian FI for which the model is calibrated in Section 4. Generalizing the model is straightforward as 1) private sector stakeholders frequently evaluate unregulated MSME lenders by their capital ratios, and 2) lender solvency (i.e., positive equity) is a specific universal minimum capital requirement.

Additionally, regulatory intervention is modeled as reducing the lender’s welfare but does not impose financial penalties (e.g., requiring a recovery plan or a change in board members, etc., as described in The U. S. Office of the Law Revision Counsel, 2013). This approach avoids confounding the financial consequences of a disaster from those of regulatory intervention, The model can be directly extended to include financial penalties, which if assumed, increase the cost of the disaster and further delay recovery.

3.1. Model

A lender attempts to maximize its income over an infinite horizon. This lender manages a stock of equity capital $K_t$ and is unable to attract additional equity investments. Each period, the lender begins with a portfolio of one-period loans $L_t$ that are about to mature. The lender can originate new one-period loans $l_t$ at a given interest rate $r$ or invest in other FIs and receive a risk-free return $r_f$. The lender can also choose to lend more than its current equity by borrowing at the risk-free rate. Lending is exposed to the production risks of borrowers including those associated with a large natural disaster, leading to an exogenous, random nonrepayment rate $\xi_{t+1} \in [0, 1]$. Thus, the level of outstanding loans that transfer to the next period is $L_{t+1} = (1 - \xi_{t+1})l_t$.

Additionally, the lender incurs operational costs $h(K_t, l_t)$. These costs are separable. Some are a function of its state ($K_t$), overhead costs such as back-office labor and real estate costs, bank
licensing and regulatory fees, etc.\textsuperscript{2} Other costs are a function of its actions ($l_t$) – information and origination costs associated with selecting and and monitoring borrowers. These information and origination costs are convex in lending. Finally, the lender adjusts its value based on loan losses $\xi_{t+1}l_t$. Thus, its income function is

$$\pi_{t+1} = (1 - \xi_{t+1})rl_t - rf_{dl} - h_t - \xi_{t+1}l_t$$

where $d_t \equiv l_t - K_t$. If $d < 0$, the lender is a net creditor to other FIs; if $d > 0$, it is a net debtor. All earnings are retained; lender equity evolves following

$$K_{t+1} = K_t + \pi_{t+1}.$$  

The lender is monitored by its capital ratio $K_t/L_t$. If the lender’s capital ratio falls below the minimum requirement $\kappa$, the supervisor responds with increasingly invasive interventions that the lender finds undesirable. This penalty is represented as

$$g(K_t, L_t) = \nu \max\{0, \kappa - K_t/L_t\}^2 L_t.$$  

Given these conditions, the lender’s problem is

$$\max_{l_t \geq 0} \sum_{t=1}^{\infty} \delta^{t-1}E[\pi_t - g_t]$$

where $\delta$ is the discount rate.

### 3.2. Model mechanics

The model structure limits describing it analytically. Section 4 provides a numerical illustration of the dynamic, stochastic version; here, I use several heuristics from simplified versions of the model to offer some intuition regarding its mechanics and the paper’s hypotheses. First, I use the dynamic deterministic version by setting $E[\xi_{t+1}] \equiv \bar{\xi}$ and drop time subscripts. Second, I use a single-period, stochastic version for which the lender’s problem is

$$\max_{l \geq 0} E[\pi(K, l) - g(K, l)].$$

**Risk hypothesis:** Disaster risk reduces lending. For the deterministic model, the first order condition is

$$V_l : (1 + \delta \lambda)\pi_l - g_l \leq \mu$$

$$l \geq 0, \mu \leq 0, l > 0 \implies \mu = 0$$

\textsuperscript{2}In the numerical example, I assume that these costs are linear in $K$ without loss of generality.
where $\lambda$ is the shadow price of capital and the notation $\pi_t$ indicates $\partial \pi / \partial l$. This result is similar to the single-period, stochastic optimization of (4), $E[\pi_t - g_t] \leq \mu$, except that the dynamic optimization more strongly weights the income effect of lending as it influences its future state.

The optimal lending policy results in

$$\left(1 - \bar{\xi}\right) r - r_f - \bar{\xi} = \begin{cases} h_t & \text{if } K/L > \kappa \\ h_t + g_t/(1 + \delta \lambda_t) & \text{o.w.} \end{cases}$$

(6)

for cases with an interior solution, which is the focus hereafter. The left hand side shows the net marginal financial return on lending and is a constant, and the right hand side includes marginal costs increasing in $l$. The first row shows that in some cases (e.g., lenders facing sufficiently steep costs relative to their net financial margin), the optimal lending policy is not affected by capital scarcity in the long run. In these cases, capital still constrains lending when these lenders have not reached their steady state level. The second row describes lending on their optimal growth path, which shows that the consequences of operating below minimum capital requirements reduce lending.

In other cases, the optimal lending policy is always governed by the second row; capital constrains lending on the optimal path and at the steady state. The average lending growth rate is 30% for the large panel of MSME lenders in developing and emerging economies discussed in Section 5. These lenders are clearly on a growth path. If the model describes them, capital constraints influence lending regardless of their potential steady state.

The first order condition of the single-period, stochastic problem results in a lending policy governed by

$$(1 - E[\xi]) r - r_f - E[\xi] = \begin{cases} h_t & \text{if } E[g] = 0 \\ h_t + E[g] & \text{o.w.} \end{cases}$$

Capital constrains lending if the possibility of falling below minimum capital requirements is nonzero for any outcome. This result provides support for Hypothesis 1 – the risk of capital losses reduces lending, even when lenders operate above minimum requirements.

Response hypothesis: Disaster shocks reduce lending due to capital constraints. Disasters reduce equity through loan losses. Relying on the dynamic, deterministic model, I examine the effect of an equity shock on lending. By the implicit function theorem

$$\frac{\partial l}{\partial K} = - \frac{V_{1K}}{V_{1l}}$$

where $V_{1K}$ and $V_{1l}$ are the derivatives of the first order condition with respect to $K$ and $l$. $V_{1l}$ is negative as it describes deviations from the optimal lending policy where $V_l = 0$. If the lender

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3Deriving the first order condition may be facilitated by formulating the lender’s problem with the deterministic Bellman equation $V(K_t) = \max_{l_t \geq 0} \pi_{t+1}(K_t, l_t) - g_{t+1}(K_t, l_t) + \delta V(K_{t+1})$. The first order condition is

$V_{t,l} : \pi_{t+1,l} - g_{t+1,l} + \delta \lambda_{t+1} K_{t+1,l} \leq \mu_t$

$= s_{t+1,l} - g_{t+1,l} + \delta \lambda_{t+1} s_{t+1,l} \leq \mu_t$

where $\lambda_t \equiv V_{K_{t+1}}$. 10
was operating with large buffer of capital above minimum requirements before the equity shock, its optimal policy may be governed by the first row of (6) for which \( V_{lK} = 0 \) and so \( \partial l / \partial K = 0 \).

Otherwise, the derivative of Equation (6) with respect to equity is

\[
V_{lK} = -g_{lK} = \frac{\nu}{(1 - \xi)^2} (1 + r_f - h_k) (K + \pi - \pi_l).
\]

(7)

\( V_{lK} \) is the product of three terms. The first is positive. The second term is positive as long as single-period overhead costs do not exceed the lender’s equity, which would seem to be almost universally true in practice. The third term is also positive as \( \pi \approx \pi_l \). Thus, \( V_{lK} \) is positive and so \( \partial l / \partial K > 0 \). This result provides support for Hypothesis 2 – through capital constraints, disaster shocks can be expected to reduce lending.

4. Application in Peru: MSME lending under severe flood risk

This section calibrates the model with an illustrative case, El Niño related flooding and its effects on MSME lending in northern Peru. The model simulation results are consistent with the experience of MSME lenders in Peru during the 1998 El Niño, which is discussed at the end of the section. Appendix A provides supporting material including additional details regarding the model calibration and the estimation of the probability of a severe El Niño.

El Niño events are the result of a disruption in oceanic and atmospheric circulation along the equatorial Pacific. This disruption creates a massive warm from that results in three to four months of torrential rainfall and flooding in northern Peru and southern Ecuador (Lagos et al., 2008). The most recent severe El Niño events occurred in 1998 and 1983. Both caused rainfall of roughly 40 times the average for January to April (Skees and Murphy, 2009). Because of the geophysical process leading to severe El Niño, Pacific ocean temperatures are the primary measure of El Niño used by climate scientists (e.g., Wolter and Timlin, 1998) and the metric used in this study. I estimate the annual probability of a severe El Niño to be 4.6%.

The FI for which the model is calibrated is a deposit-taking institution with an average loan size of USD 1,600 and a credit portfolio of over USD 500 million. Ninety five percent of its revenues come from direct lending to non-financial firms and households. Similar to its peers, the FI initially specialized geographically and has expanded from those regional offices.

The model is calibrated using monthly income and balance sheet data from July 2009 to June 2012 as the evaluation period. Unless otherwise specified, the values in Table 1 reflect averages from this period. For example, its average annual lending interest rate is 40%, which is consistent with other MSME lenders in Peru. During the evaluation period, the regulating supervisor required this type of FI to maintain a capital ratio of at least 14%.

The FI surveyed its office and credit risk managers in the vulnerable region regarding their perceived credit exposure to severe El Niño (n=27). Roughly 20% of its portfolio is in this region. The most vulnerable reported sectors, with average expected loan losses for each in parentheses, are agriculture (33%), commerce (i.e., firms in retail, 23%), transportation (21%), and fishing (16%). In total, the FI expects to lose 15% of the value of its loans in the vulnerable region, approximately 3.5% of its total loan portfolio. If a severe El Niño occurs. This estimation seems plausible given
Table 1: Calibration summary, annualized values

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<th>Parameter</th>
<th>Symbol</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lending interest rate</td>
<td>$r$</td>
<td>40%</td>
</tr>
<tr>
<td>Risk free rate</td>
<td>$r_f$</td>
<td>4.25%</td>
</tr>
<tr>
<td>Origination expense (% of loans)</td>
<td>$\alpha$</td>
<td>2%</td>
</tr>
<tr>
<td>Information expense (% of squared loans)</td>
<td>$\beta$</td>
<td>0.2%</td>
</tr>
<tr>
<td>Overhead expense (% of equity)</td>
<td>$\gamma$</td>
<td>10%</td>
</tr>
<tr>
<td>Discount rate</td>
<td>$\delta$</td>
<td>95.75%</td>
</tr>
<tr>
<td>Minimum capital requirement</td>
<td>$\kappa$</td>
<td>14%</td>
</tr>
<tr>
<td>Regulatory penalty</td>
<td>$\nu$</td>
<td>5</td>
</tr>
<tr>
<td>Expected nonrepayment rate (nondisaster)</td>
<td>$\eta$</td>
<td>3.0%</td>
</tr>
<tr>
<td>Standard deviation of nonrepayment (nondisaster)</td>
<td>$\sigma$</td>
<td>0.24%</td>
</tr>
<tr>
<td>Disaster nonrepayment</td>
<td>$\psi$</td>
<td>3.5%</td>
</tr>
<tr>
<td>Disaster probability</td>
<td>$P[c_{t+1} \geq 24.5]$</td>
<td>4.6%</td>
</tr>
</tbody>
</table>

the experience of similar lenders during the 1998 event, as discussed in Appendix B and (Collier et al., 2011).

4.1. Results: MSME lending in Peru

This section describes the modeled optimal behavior of the lender and examines the effects of a natural disaster on its operations.

Non-disaster simulation. Non-disaster simulations test how lending responds to the possibility of a disaster and so provides evidence related to the Risk Hypothesis, that disaster risk reduces the supply of credit by local lenders. I compare model performance with the actual performance of the lender during the evaluation period through Monte Carlo simulations. These tests rely on the assumption that, aside from El Niño, which did not occur during that time, the evaluation period provides a good approximation of the distribution of loan losses. MSME lenders in developing and emerging economies are frequently recognized as insulated from the macroeconomy and more vulnerable to local conditions (e.g., BCBS, 2010). It is conceivable that systemic credit risk may be due to a discrete, local shock other than El Niño and that this shock also did not occur in the evaluation period. If so, the model would attribute risk management strategies to El Niño that may address other risks as well.

The model is calibrated for quarters; El Niño occurs over a period of roughly three months in Peru and so is captured in a single period. The calibration period is 12 quarters in duration. I run a 12 quarter simulation 100,000 times. To make its results comparable to the evaluation period, a time when we know ex post that no disaster occurred, I exclude disasters from the simulation, though the lender behaves as if a disaster could occur in any period. Stochastic performance is driven by the unexplained variation in loan losses $\varepsilon$ modeled in (8).

The mean capital ratio is 15.8% for the FI for which the model is calibrated. The simulation also results in a mean capital ratio of 15.8% when the parameter for the penalty function is set at $\nu = 5$. I use this parameter value for the disaster simulation below and show alternative specifications in a sensitivity analysis.
The simulation explains lender behavior as a function of risk and capital constraints, which lead to a 1.8 percentage point buffer above the minimum requirement of 14%. This buffer comes at a cost to local credit supply. Rerunning the simulations without the disaster risk results in a mean capital ratio of 14.5% and a 10% expansion of the local credit market.

**Disaster simulation.** Disaster simulations test the Response Hypothesis, that disasters reduce lending due to capital constraints. The disaster creates loan losses that reduce lender equity 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 reducing credit supply.

Figure 4.1 illustrates model results for a disaster simulation. In the figure, the disaster occurs in Period 0. Eight quarters precede; 20 follow it. Initial values are set at the mean of the steady state distribution. To isolate the effect of the disaster, I set the unexplained variation in nonrepayment from (8) equal to its mean, \( \varepsilon = 0 \). The dotted gray lines capture this unexplained variation and represent 95% confidence intervals for each period based on \( \text{var}(\varepsilon) \). The y axes for equity and loans are scaled based on the mean values of their steady state distributions. The y axis for the penalty is written as a percent of average steady-state revenues and so shows that the lender would value the regulatory intervention as equivalent to a loss of 1.5% of revenues.

The seemingly small loss of 3.5% of the loan portfolio represents about 22% of the lender’s equity, leading to a credit contraction of about 15% of its pre-event level. Credit contraction persists after the capital ratio rises above regulated minimums. It is the lender’s internal capital targets, which are a function of its risk and the severity of the capital penalty, that guide this behavior so that even if loan losses lead to a capital decline that remains above minimums, credit contraction occurs.

4.2. **Implications of regulatory stringency**

This section explores the effect of the capital ratio penalty on the optimal lending policy and serves as a sensitivity analysis. Figure 4.2 shows the effect of regulatory stringency on the optimal lending policy and capital ratio by examining a range of values for \( \nu \). (In the simulations above, \( \nu = 5 \).) The figure illustrates an important social tradeoff for policymakers. Stringent supervision increases the lender’s target capital ratio, reducing the risk that a large systemic event would lead to insolvency. Moreover, stringent supervision motivates a rapid response from the lender to a falling capital ratio, which seems particularly important for supervisors who have imperfect information regarding portfolio quality. Such stringency, however, also reduces total loan supply and increases credit contraction when a disaster occurs.

4.3. **Credit supply and the 1998 El Niño, an example**

Appendix B provides an illustrative case from the 1998 El Niño, developed through interviews and analysis of the financial performance of a large MSME lender and commercial banks in Peru. It compares Caja Trujillo, the largest MSME lender in its region, providing over 60% of all credit from regulated FIs, with that of commercial lenders, which lent to large firms and were headquartered in Lima, Peru’s capital city located several hundred kilometers from the floods. Both commercial lenders and Caja Trujillo reduced lending in the region from January to April 1998, the period of
catastrophic flooding, likely a time when little formal economic activity occurred. Loan losses and concern about portfolio quality motivated Caja Trujillo to reduce lending to its MSME borrowers, contracting credit by about 12% from pre-event levels at its lowest; however, credit from commercial banks increased by 25% to meet the demand of large firms. Figure 4.3 compares the percent change in loan allocations from commercial banks to those of Caja Trujillo. This increased credit gap remained until approximately May 1999, roughly a year after the torrential rains ended.

5. MSME lender panel

This section generalizes from the modeled case in Peru to evaluate the effects of natural disasters on credit supply using a panel of MSME lenders from developing and emerging economies around the world. The reduced form models estimate loan growth as a function of disaster severity and the lender’s capital ratio. Supporting the Response Hypothesis, results indicate that disasters significantly reduce lending and can largely be explained by capital constraints.
Figure 2: Supervisory stringency, capital targets, and lending
Note: More stringent capital requirements are operationalized as higher levels of $\nu$.

Figure 3: Loans from commercial banks and Caja Trujillo in La Libertad
Note: Following El Niño, commercial banks expanded credit by approximately 25% in La Libertad to meet the needs of its customers, mostly large firms. In contrast, capital management related to loan losses challenged the ability of Caja Trujillo to meet the demands of its MSME customers. The y axis is set so with reference to the size of loan allocations in December 1997, just prior to catastrophic flooding.

5.1. Methods: MSME lender panel

MIX Market (2014) provides voluntarily reported annual income and balance sheet information from MSME lenders in developing and emerging economies, starting in 1995. The longest panels are for 18 years; the median is 4 years. Data for each FI are reported annually and for consecutive years (i.e., FIs are not included that omit a year between the initial and final years reported). For 2011, these FIs collectively held $91 billion in loans and lent to 93 million borrowers. The outcome of interest is the year-on-year growth in the face value of the loan portfolio – the total value of outstanding loans before accounting for write-downs in loan value due to poor performance.

EM-DAT (2014) compiles data on the consequences of natural disasters (e.g., the number of people affected by an event) from a variety of sources (governments, nongovernmental organizations,
media coverage, etc.) on the consequences of natural disasters. The included natural disasters are, in order of frequency, flood, storm, earthquake, drought, land slide, wildfire, and volcanic activity. These data are reported at the country level and include 7,700 events from 215 countries between 1995 and 2013. Merging these data with the MIX Market data, I calculate the percent of a country’s population affected by natural disasters in a given year. Each MSME lender in the same country-year has the same observation of disaster severity.

The analyses additionally include control variables from MIX Market data (e.g., lender assets), but also data from the World Bank on per capita GDP, inflation, and governance indicators. I also include three measures of the public institutional environment from the Worldwide Governance Indicators: Regulatory Quality, Political Stability and Absence of Violence, and Voice and Accountability (Kaufmann et al., 2010, 2014). All included controls are modeled using one and two-year lags to avoid confounding the current-period effects of disasters (e.g., current-year per capita GDP may be influenced by disaster losses).

Data representativeness is worthy of consideration. Regarding MIX Market, the primary benefit of reporting to lenders is likely greater international visibility. These lenders may have more sophisticated management information systems and performed better in recent years than their non-reporting peers. Also, the sample includes surviving lenders and so does not generally account for those that became insolvent due to a natural disaster or other event. Regarding EM-DAT, government and non-government reports of disasters may be influenced by the incentives of the reporter (e.g., political pressure might motivate certain regimes to downplay economic losses). EM-DAT attempts to minimize such effects by confirming losses through several sources. Also, countries with greater media coverage and freedoms may be more likely to report disasters.

Following Wooldridge (2002) and Drukker (2003), I test for serial correlation in the errors of the linear panel model, rejecting the null of no first-order autocorrelation. As a result, all models use first-difference estimators in the analyses with standard errors clustered at the country level and fixed effects for years. The merged data include 1,321 lender-year observations from 58 developing and emerging economies between 1995 and 2013. Table 2 provides a description of each variable. All values are in current year U.S. dollars.

Table 3 shows means and percentiles for the variables of interest: loan growth, disaster effects, and the capital ratio. Median annual loan growth in the data is 24.6%. Loan growth for the top one percent of FIs describes newly established lenders; the bottom one percent are effectively insolvent. The percentage of individuals affected by disasters is highly nonlinear; at the median, natural disasters affect 0.5% of a country’s population each year. The capital ratio includes minimum values of effectively insolvent lenders and maximum values for fully capitalized lenders. The median capital ratio for this sample, at 31.9%, is consistent with an explanation of large portfolio concentrations of risk and limited access to external capital. These large capital buffers could be explained by

4 Changes in the inflation rate may be most relevant in modeling loan growth. I use the inverse hyperbolic sine transformation, which approximates a log transformation but is defined over non-positive values.

5 EM-DAT (2014), MIX Market (2014), and Kaufmann et al. (2014) provide detailed reporting on their data and methodology.
Table 2: Variables included in first-difference regression models

<table>
<thead>
<tr>
<th>Variable</th>
<th>Explanation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Loans</td>
<td>Value of all loans made by the FI before adjusting for loan quality</td>
</tr>
<tr>
<td>Disaster severity</td>
<td>Number of people affected by natural disasters/population in a given year</td>
</tr>
<tr>
<td>Capital ratio</td>
<td>Equity/loans</td>
</tr>
<tr>
<td>Assets</td>
<td>Value of all FI assets</td>
</tr>
<tr>
<td>Liquidity ratio</td>
<td>Non-earning liquid assets/assets</td>
</tr>
<tr>
<td>Write-off ratio</td>
<td>Loans deemed uncollectible/loans</td>
</tr>
<tr>
<td>GDP per capita</td>
<td>GDP/population</td>
</tr>
<tr>
<td>Inflation</td>
<td>Changes in the Consumer Price Index.</td>
</tr>
<tr>
<td>Regulatory quality</td>
<td>Degree to which government policies and regulations are conducive to private sector development</td>
</tr>
<tr>
<td>Political stability &amp; effectiveness</td>
<td>The likelihood of government destabilization by unconstitutional or violent means</td>
</tr>
<tr>
<td>Voice &amp; accountability</td>
<td>Degree to which a country’s citizens can participate in selecting their government, as well as freedom of expression, freedom of association, and a free media.</td>
</tr>
</tbody>
</table>

All values are in current year U.S. dollars. Lender, disaster, national accounts, and governance data are respectively from MIX Market (2014); EM-DAT (2014); World Bank (2014); Kaufmann et al. (2014).

Table 3: Means and percentiles for variables of interest

<table>
<thead>
<tr>
<th>Percentile</th>
<th>Mean</th>
<th>1st</th>
<th>25th</th>
<th>50th</th>
<th>75th</th>
<th>99th</th>
</tr>
</thead>
<tbody>
<tr>
<td>Δlog(loans)</td>
<td>30.6</td>
<td>-83.8</td>
<td>7.1</td>
<td>24.6</td>
<td>45.6</td>
<td>225.1</td>
</tr>
<tr>
<td>Disaster severity</td>
<td>2.5</td>
<td>0</td>
<td>0.04</td>
<td>0.5</td>
<td>2.2</td>
<td>27.4</td>
</tr>
<tr>
<td>Capital ratio</td>
<td>38.1</td>
<td>1.4</td>
<td>18.9</td>
<td>31.9</td>
<td>53.9</td>
<td>98.0</td>
</tr>
</tbody>
</table>

All values are percentages.

disaster risk as well as a variety of other undiversifiable credit risks.

5.2. Results: MSME lender panel

Table 4 provides the model results for the direct effect of disasters on loan growth. The first column measures disaster severity using the percent of the population affected and indicates that disasters significantly reduce lending in the following year. The effect of disasters is best interpreted at the country level as the disaster may or may not occur in the same area of the country in which a lender operates. These are a lower bound estimate for individual lenders. Thus, on average, this sample suggests that countries experiencing a one percent increase in the population affected by disasters can expect a 0.45 percentage point reduction in loan growth for markets served by MSME lenders.

In the second column, I test for nonlinear effects of disasters by “binning” disaster severity by quartile, creating a set of dummies across percentiles of severity. The results show larger and sustained lending reductions for more severe disasters. For example, this sample suggests that a country experiencing disaster effects in the highest quartile of severity is likely to have an 11 percentage point reduction in MSME loan growth in the same year and an 8 percentage
point reduction in loan growth the following year. In most cases, every country experiences a natural hazard of some form, only 12% of the time is none of the population affected by a disaster. Therefore, the reference group in column two includes lenders in countries experiencing no disasters or disasters falling in the first quartile of severity.

Disasters may influence lending through three channels by changing: demand, the willingness of lenders to lend, and/or the capacity of lenders to lend (capital or liquidity constraints). Table 5 examines the degree to which lending reductions following disasters may be explained by capital constraints and finds a significant interaction between the capital ratio and disaster effects. In the first column, I center and interact disaster severity and the capital ratio. I also test the liquidity ratio but find no evidence it significantly reduces lending following a disaster. Main effects for the capital and liquidity ratios are also included but are not significant.

The significant interaction terms are difficult to interpret so in the second column, I explore them by dividing lenders into terciles based on their capital ratios. The first tercile includes lenders whose capital ratios are below 22%; the third includes lenders with capital ratios above 46%. The results from the second column support Hypothesis 2 and the model results, that capital constraints reduce lending after a disaster. Lenders with the lowest pre-disaster capital ratios significantly reduce lending in the year a disaster occurs and in the following year. Lenders in the second tercile lend less but only in the year following the event. Loan growth for those in the top tercile is not significantly affected by disasters.

I explore several alternative explanations for these results in Appendix C. These tests consider whether credit contraction for low capital lenders following disasters is, instead of capital constraints, explained by observable differences between lenders with low and high capital ratios in terms of 1) lender size, 2) borrower size, 3) country development, and 4) regulatory quality. The results suggest important differences across contexts, but support the main finding that capital constraints seem to reduce lending following a natural disaster in this sample. The appendix also includes a GMM linear panel estimation to assess for dynamic panel bias and potential endogeneity. That model’s results are qualitatively consistent with the first difference models presented here.

A question of interest is what causes the one-period delay in transmitting disaster effects to reduced loan growth in some of the specifications above. While more research is needed, one potential answer is that some lenders may delay write-downs through borrower grace periods and loan restructuring and so may not feel the full effect of capital losses due to a disaster until the following year, allowing them to augment capital via retained earnings. This behavior is evident in the case study in Appendix B. Appendix C shows that lenders with low capital ratios that are large, in more developed countries, or in countries with better regulatory quality are more likely to report immediate reductions in lending following disasters. Earnings manipulation, when discovered, has been shown to increase financing costs (Dechow et al., 1996) and may explain this effect. Larger lenders in better regulated and/or more developed markets, which are presumably more likely to be caught if they manipulate their financials, may face greater incentives to report losses and respond to capital constraints quickly.
Table 4: First difference model of log(loans), main effects

<table>
<thead>
<tr>
<th></th>
<th>Continuous</th>
<th>Binned (binary)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Disaster severity$_{t}$</td>
<td>-0.217</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.222)</td>
<td></td>
</tr>
<tr>
<td>Disaster severity$_{t-1}$</td>
<td>-0.447**</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.170)</td>
<td></td>
</tr>
<tr>
<td>Disaster severity$_{t-2}$</td>
<td>-0.0197</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.126)</td>
<td></td>
</tr>
</tbody>
</table>

2nd quartile

<p>| | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Disaster$_{t}$</td>
<td>-0.0636**</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0290)</td>
<td></td>
</tr>
<tr>
<td>Disaster$_{t-1}$</td>
<td>-0.0312</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0334)</td>
<td></td>
</tr>
</tbody>
</table>

3rd quartile

<p>| | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Disaster$_{t}$</td>
<td>-0.0910***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0264)</td>
<td></td>
</tr>
<tr>
<td>Disaster$_{t-1}$</td>
<td>-0.0669***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0235)</td>
<td></td>
</tr>
</tbody>
</table>

4th quartile

<p>| | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Disaster$_{t}$</td>
<td>-0.107***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0227)</td>
<td></td>
</tr>
<tr>
<td>Disaster$_{t-1}$</td>
<td>-0.0773**</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0315)</td>
<td></td>
</tr>
</tbody>
</table>

Observations 1321 1321

Adjusted $R^2$ 0.245 0.253

Standard errors in parentheses

* $p<0.10$, ** $p<0.05$, *** $p<0.01$

Model of log(loans) using first difference estimator with standard errors clustered at the country level. Model includes fixed effects for years. The outcome variable is the total value of the MSME lender’s outstanding loan portfolio before accounting for write-downs in loan value due to poor performance. In the first column, the disaster measure is a continuous variable of the number individuals affected by a disaster divided by the population. In the second column, the disaster measure is binary. The reference group is lenders in countries experiencing no disasters or disasters falling in the first quartile of severity. The disaster measures are the only explanatory variables using current period values; all other variables use one and two-year lags to avoid confounding the effects of disasters. Control variables include lender capital, liquidity, and write-off ratios; log(Assets); log(GDP per capita); inflation; regulatory quality; political stability; and accountability.
Table 5: First difference model of log(loans), main effects and interactions

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Testing interactions</td>
<td>Exploring capital interactions</td>
</tr>
<tr>
<td>Disaster severity(_t)</td>
<td>-0.166</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.242)</td>
<td></td>
</tr>
<tr>
<td>Disaster severity(_{t-1})</td>
<td>-0.458***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.165)</td>
<td></td>
</tr>
<tr>
<td>Disaster severity(_{t-2})</td>
<td>-0.00259</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.134)</td>
<td></td>
</tr>
<tr>
<td>Capital ratio</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Disaster(<em>t):Capital ratio(</em>{t-1})</td>
<td>1.765**</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.801)</td>
<td></td>
</tr>
<tr>
<td>Disaster severity(<em>{t-1}):Capital ratio(</em>{t-2})</td>
<td>1.778***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.458)</td>
<td></td>
</tr>
<tr>
<td>Capital ratio, 1st tercile</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Disaster severity(_t)</td>
<td></td>
<td>-0.694***</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.255)</td>
</tr>
<tr>
<td>Disaster severity(_{t-1})</td>
<td></td>
<td>-0.737***</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.147)</td>
</tr>
<tr>
<td>Capital ratio, 2nd tercile</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Disaster severity(_t)</td>
<td></td>
<td>-0.0982</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.239)</td>
</tr>
<tr>
<td>Disaster severity(_{t-1})</td>
<td></td>
<td>-0.570***</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.139)</td>
</tr>
<tr>
<td>Capital ratio, 3rd tercile</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Disaster severity(_t)</td>
<td></td>
<td>0.115</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.434)</td>
</tr>
<tr>
<td>Disaster severity(_{t-1})</td>
<td></td>
<td>-0.114</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.169)</td>
</tr>
<tr>
<td>Liquidity ratio</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Disaster severity(<em>t):Liquidity ratio(</em>{t-1})</td>
<td>0.105</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.751)</td>
</tr>
<tr>
<td>Disaster severity(<em>{t-1}):Liquidity ratio(</em>{t-2})</td>
<td>0.286</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.598)</td>
</tr>
<tr>
<td>Observations</td>
<td>1314</td>
<td>1314</td>
</tr>
<tr>
<td>Adjusted (R^2)</td>
<td>0.245</td>
<td>0.246</td>
</tr>
</tbody>
</table>

Standard errors in parentheses

* p<0.10, ** p<0.05, *** p<0.01

Model of log(loans) using first difference estimator with standard errors clustered at the country level. Model includes fixed effects for years. The outcome variable is the total value of the MSME lender’s outstanding loan portfolio before accounting for write-downs in loan value due to poor performance. In the first column, I center and interact disaster severity and the capital ratio as well as disaster severity and the liquidity ratio. The second column explores the significant interaction between disaster severity and the capital ratio by dividing lenders into terciles based by capital ratio. For example, lenders with the lowest pre-disaster capital ratios significantly reduce lending following a disaster while lenders in the top tercile do not. The disaster measures are the only explanatory variables using current period values; all other variables use one and two-year lags to avoid confounding the effects of disasters. Main effects for the capital and liquidity ratios are included; none are significant. Additional control variables include lender write-off ratios, log(Assets), log(GDP per capita), inflation, regulatory quality, political stability, and accountability.
6. Strengthening community credit markets through disaster-contingent claims

A variety of private and public sector interventions are used around the world that can potentially reduce the consequences of severe climate risks in MSME credit markets. Promising and seemingly successful cases exist (e.g., see an overview of credit guarantee programs from Beck et al., 2010; Saadani et al., 2011). A challenge for public programs in particular is to avoid rewarding risk taking that would perpetuate or even increase disaster vulnerability (Mileti et al., 1999). This challenge is exacerbated by the same information problems that limit access to credit for MSMEs. For example, Levitsky (1997) note that moral hazard is a central concern for government-sponsored SME lending programs. Kunreuther and Pauly (2006) conclude that one factor reducing demand for flood insurance is moral hazard created by expectations of future government relief. Just et al. (1999) and Smith and Goodwin (1996) analyze government-subsidized agricultural insurance markets in the U.S and find evidence of adverse selection and moral hazard. Hazell (1992) concludes that government-supported, indemnity-based agricultural insurance markets in developing and emerging economies are generally not sustainable due to asymmetric information.

The seminal work of Diamond (1984) on lending under opacity offers a potential alternative (or complement) that can be tested in Peru. Diamond argues that if the returns of opaque borrowers are correlated with an observable risk (e.g., interest rate risk), contingent contracts should be used to transfer the lender’s systemic risk. Recently, a contingent contract for El Niño was developed in Peru that would seemingly allow for hedging in the way Diamond describes. As a final exercise, I extend the model to evaluate this contingent contract and its potential effect on lender behavior.

The contingent contract in Peru is a parametric insurance product, which makes payments not on policyholder losses, but based on an objective measure of El Niño. Basing payments on the observable risk of a severe disaster reduces moral hazard and adverse selection relative to indemnity based insurance (Barnett and Mahul, 2007; Miranda, 1991; Skees and Murphy, 2009). This type of hedge is vulnerable to basis risk, which in this case is a discrepancy between the severity of the disaster as experienced by the FI and that as measured by the index used for payouts.

The El Niño insurance uses the same measure of the event as discussed in Section 4 as the sole basis of payments, the Niño 1+2 index of ocean temperatures. The contracts offered in Peru typically have a linearly increasing payout structure. For example, one contract has a trigger of 24.5°C and exhaustion point at 27°C, where the full sum insured is paid. Following my treatment of El Niño as a binary event, I use a simplified contract structure such that the full sum insured is paid if severe El Niño occurs, leading to the payout function

\[ i(c_{t+1}) = \begin{cases} 
1 & \text{if } c_{t+1} \geq \bar{c} \\
0 & \text{o.w.} 
\end{cases} \]

where \( c_{t+1} \) is the measure of ocean temperature and \( \bar{c} = 24.5°C \). Discussions with insurers and reinsurers suggest that for this risk the loads for commissions, administration costs, etc., would be

\(^6\)While this contract is regulated as insurance in Peru, it has the potential to take other forms elsewhere (e.g., an option contract or catastrophe bond).
approximately 75% of the actuarially fair rate, resulting in an annual premium rate of 8.05% of the sum insured for the loaded, stylized contract, a rate in the vicinity of the contracts in Peru, which range from approximately 7-11% of the sum insured.\footnote{For readers interested in learning more about the El Niño insurance, which has several interesting features, please see The Economist (2014); GlobalAgRisk (2013).}

6.1. Model with insurance

As an update to the dynamic model, the lender can buy a sum insured $q_t \geq 0$ at premium rate $p_t$ and receive a payout based on the function $i(c_{t+1})$. The lender’s new income equation is

$$\pi_{t+1} = r(1 - \xi_{t+1})l_t - r_f d_t - h_t - \xi_{t+1}l_t - pq_t + q_t i(c_{t+1}).$$

Figure 4 illustrates the results, showing that transferring disaster risk increases the credit supply during non-disaster conditions and reduces credit contraction following disasters. The dotted blue line replicates the disaster simulation from Section 4.1, the dotted purple line represents the case in which the insurance is priced at the actuarially fair rate, and the solid green line represents the case in which the insurance is priced at the rate observed in the Peruvian market.

At the actuarially fair rate, the lender fully insures the credit and revenue exposure. At the loaded rate and current calibration, the lender insures 47% of the credit and revenue exposure before the event; however, during recovery, when the lender is more vulnerable to additional capital losses, it insures up to 60% of its credit and revenue exposure. When the disaster occurs, the insurance payout offsets loan losses and so smooths lender income, protecting its equity, stabilizing the capital ratio, and dramatically reducing credit contraction. Because the insurance addresses the disaster-related credit risk, the lender operates with a smaller buffer above minimum requirements. Under the actuarially fair case, loan allocations increase by 8.5% under non-disaster conditions, 5% in the loaded case.

Figure 4: Simulation results of severe flood on lender operations, insured and uninsured cases.
6.2. Implications for bank holding companies.

While the focus of this research is independent MSME lenders, these results are also relevant to bank holding companies. Rather than using external insurance markets, bank holding companies might formally integrate disaster-contingent claims in their internal capital markets. While not studying natural disasters, De Haas and Van Lelyveld (2010) find that, in the midst of a local banking crisis, subsidiaries with international parents keep lending based on their access to additional capital if it is needed. The model with insurance seems to explain this behavior well—the expectation of capital relief motivates reducing capital buffers to increase lending. Profit maximization requires that the transfer price of this contingent claim be based on the expected cost (Hirshleifer, 1956), the actuarially fair price for the insurance, as shown in Figure 4; without such internal pricing, disaster-contingent claims create perverse incentives for subsidiaries. For bank holding companies whose subsidiaries are transparent, these internal markets can be indemnity oriented, providing capital infusions based on portfolio quality, which can be communicated across the hierarchy with hard information. For bank holding companies with opaque subsidiaries, disaster-related capital transfers based on an observable trigger would better align the incentives of the parent and subsidiary (Diamond, 1984; Stein, 2002).

7. Discussion

This paper provides a theory to explain the challenges faced by MSME credit markets in communities vulnerable to severe climate and other disaster risks. While large banks manage disaster risk via geographic diversification and integration in international markets, evidence suggests that these approaches are quite difficult for MSME lenders due to the information problems associated with lending to their clients. The theory predicts that following a disaster, when communities would benefit substantially from credit, these markets are poorly equipped to provide it. It also predicts that credit access during non-disaster conditions in vulnerable communities is significantly reduced because lenders cannot effectively manage disaster risk. Evidence from a dynamic, theoretical model for a lender vulnerable to flood risk in Peru and a panel analysis of MSME lenders from developing and emerging economies around the world support this theory.

Perhaps the most pressing policy implication of this work is the importance of technologies that increase hard information available to lenders. MSME credit markets in the U.S. have rapidly changed due to these technologies, increasing competition and participation of commercial banks in these markets (Petersen and Rajan, 2002; Agarwal and Hauswald, 2010). As Berger and Udell (2006) note, a variety of mechanisms allow for lending in the SME sector (e.g., trade credit, factoring, etc.), largely based on alternative forms of collateral. Thus, policies that improve contract enforcement and formalize property rights may also contribute to this objective (e.g., see Clague et al., 1999; Ray, 1998).

This paper also describes contingent claims contracts as a helpful mechanism to strengthen local credit markets using El Niño insurance in Peru as an example. These mechanisms are well suited to address the disaster risks of MSME lenders as they are contracted based on an observable measure of the severe event and so are less prone to the asymmetric information problems that
likely preclude indemnity insurance in this context. The theoretical model shows that the insurance increases lending during non-disaster conditions and reduces credit contraction after a severe event. A highly regarded FI in Peru, Caja Nuestra Gente, that specializes in microfinance purchased El Niño insurance for 2012 and 2013, providing a testable case for future research.

Acknowledgments

This research is the result of collaboration with excellent professionals at Banco de Crédito del Perú, BBVA Banco Continental, Edyficar, Caja Nuestra Gente, Caja Piura, Caja Paita, Caja Sullana, La Positiva Seguros, Pacifico Seguros, Rimac Seguros, Willis Peru, and the banking regulator in Peru, Superintendencia de Banca, Seguros, y AFP. I want to especially thank Caja Trujillo for its guidance, including feedback on this manuscript. I thank Mario Miranda and Jerry Skees for their mentoring, conceptual contributions, and early reviews of this paper. Thanks also to Volodymyr Babich, Florian Berg, Grant Cavanaugh, Jason Hartell, Andrew Haughwout, Ruben Lobel, and Paul Shea for their help and insightful comments. This research was supported by the Global Centre on Disaster Risk and Poverty, the University of Pennsylvania, and the University of Kentucky. I also gratefully acknowledge support for the associated field work in Peru provided by the Bill & Melinda Gates Foundation, the United Nations Development Programme, and Deutsche Gesellschaft für Internationale Zusammenarbeit GmbH (GIZ).

A. Peru example: Supporting material

A.1. Financial performance calibration

This section provides additional details on the model calibration in Section 4 for information that could not be taken from lender’s income statements and balance sheets.

Discount and risk free rates. The risk free and discount rates are based on the interbank rate in Peru, which was 4.25% during the evaluation period.

Loan losses. The nonrepayment rate is based on the definition of default identified in Basel II, loans past due for more than 90 days (BCBS, 2006). Loan losses $\xi_{t+1} \in [0, 1]$ are modeled using the following process

$$\xi_{t+1}(x_{t+1}, \varepsilon_{t+1}) = \eta + \psi x_{t+1} + \varepsilon_{t+1}$$

where $\eta$ is the expected nonrepayment rate, $x_{t+1} = \{0, 1\}$ indicates a systemic, natural disaster, $\psi$ weights this influence based on portfolio concentration (3.5%, in this case), and $\varepsilon_{t+1}$ is unexplained variation in the realization of loan losses, which is assumed $\varepsilon_{t+1} \sim N(0, \sigma^2)$.

Operational costs. Following from Equation (2), expected profits converge to zero in the long run – convex costs eventually consume all expected revenues. Short run fluctuations over the calibration period may poorly reflect the functional forms and coefficients of long run operational costs. Out of concern for over-fitting, I take a simplified approach, using the form

$$h(K_t, l_t) = \alpha l_t + \beta l_t^2 + \gamma K_t$$
where $\alpha$ is origination, $\beta$ is information, and $\gamma$ are overhead costs and take values 0.02, 0.002, and 0.1, respectively.

The assumption that information costs are convex in loans is an important theoretical foundation, with good empirical support (e.g., Agarwal and Hauswald, 2010), regarding why MSME lenders frequently remain geographically concentrated as discussed in Section 2. The model is insensitive to assumptions regarding the functional form of overhead costs as long as these costs are greater than risk free returns. If risk free returns exceed overhead costs, the lender will hold increasingly larger amounts of risk free assets, which is not characteristic of MSME lenders in practice. I prevent this result by using a scalar $\nu$ that is greater than the risk free rate, but other approaches such as convex overhead costs are also feasible.

A.2. Probability of severe El Niño

[DEPENDING ON PAGE CONSTRAINTS, COULD BE INCLUDED AS AN ON-LINE APPENDIX]

Niño 1+2 is a monthly measure of ocean temperatures near the coast of Peru and Ecuador collected by the U.S. National Oceanic and Atmospheric Administration (NOAA). Khalil et al. (2007) find that rainfall in northern Peru is highly related to Niño 1+2. Average reported temperatures for Niño 1+2 for November and December are a strong predictor of impending torrential rains and so serve as the index of El Niño severity in this paper.

NOAA measures Niño 1+2 using a combination of data from ocean buoys, satellite sensors, and transocean liners. Data are available from 1950\(^8\); however, the amount of buoys increased significantly in the 1970s. One of the earliest reanalysis datasets, NOAA’s Climate Prediction Center Merged Analysis of Precipitation, combines rain gauge and satellite data beginning in 1979, providing validation to the other data sources comprising Niño 1+2. As a result, I use data from 1979 to 2012. Figure A.2 shows the full time series and the subset used in the 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 (Collins, 2005; Li et al., 2013; McPhaden, 2002; Merryfield, 2006; van Oldenborgh et al., 2005; Yeh et al., 2009). Regarding the 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 warm November and December temperatures of 1982 and 1997 are associated with torrential rains in January to April in 1983 and 1998 in northern Peru, respectively. Based on reasons described in Section 4, I treat severe El Niño as a binary outcome. Following discussions with climate scientists and reports on what ocean temperatures lead to significant losses in Peru, I define a temperature $c_t$ exceeding 24.5°Celsius on the Niño 1+2 Index as a severe El Niño event.

The probability of severe El Niño is assessed using maximum likelihood estimation of the generalized extreme value (GEV) distribution. This distribution is commonly used for estimating

\footnote{The data can be downloaded at cpc.ncep.noaa.gov/data/indices/ersst3b.nino.mth.81-10.ascii}
Figure 5: Niño 1+2 Index

Note: The Niño 1+2 Index is generated from the average Pacific surface temperatures in the region Niño 1+2 during November and December each year. Elevated temperatures such as those in 1982 and 1997 are associated with an impending severe El Niño. I use a subset of the total time series for which data quality is higher.

Infrequent events due to its flexibility as its parameters allow it to approximate a variety of long-tailed distributions. The results of the MLE using the Niño 1+2 index for years 1979 to 2012 suggest that a Fréchet distribution fits well, providing GEV parameters of $\mu = 21.861$, $\sigma = 0.809$, and $\kappa = 0.041$. Figure A.2 shows a histogram of the index values and the estimated probability density function. Based on this analysis, the annual probability of severe El Niño is

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

A.3. Qualitative survey results

The survey of FI credit managers and loan officers included an open-ended question asking participants whether they are concerned about the risk of a severe El Niño. The responses offer a nuanced perspective on the diverse credit risks associated with a severe flood event:

- “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 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."

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

- “We are concerned by severe El Niño...the city-level infrastructure is unable to prevent flooding because the main channel of the river runs through the city.”

**B. Case Study: Lending in northern Peru and the 1998 El Niño**

[intended for publication as an on-line appendix]

While the FI for which the model is calibrated was not operating during that event, I examine regional loan allocations for commercial banks then conduct an in-depth analysis of the largest MSME lender in one of the affected regions, Caja Trujillo. The topic of interest whether capital management seems to reduce the supply of MSME credit relative to other credit markets?

Figure B shows total loan allocations from commercial banks by region. These banks tend to be headquartered in Lima and, at this time, lent to large firms and wealthy households. As shown in Table 6, 3% of commercial bank credit was in MSME loans in January 2001, the earliest date available.
During the first quarter of 1998, loan allocations fell as El Niño-related rains and flooding affected the northern coast and Andean highlands. Given the substantial credit expansion following the event, reduced lending during this period is most readily explained by borrowers and/or commercial banks waiting until the 3-4 month period of severe rains and flooding ended to assess credit needs. Loan allocations in Lima, which is in central Peru and did not experience flooding due to El Niño, were stable during this time. In the months following the event, total loan allocations increased to levels not previously seen in the north. This expansion of large firm credit is consistent with the elevated demand for credit documented for other disasters among households (Del Ninno et al., 2003) and MSMEs (Berg and Schrader, 2012).

In Tumbes, the northernmost coastal region, severe El Niño created a longer term credit contraction among commercial banks. It is unclear whether this contraction is the result of large firms exiting Tumbes or banks being unwilling to lend there. In either case, the new information the event provided regarding El Niño risk and its consequences reduced credit investment in the region.

Caja Trujillo is the largest MSME lender in La Libertad, which is 550 km north of Lima on the Peruvian coast and the largest credit market in northern Peru. Caja is used to indicate a category of community-based deposit-taking and lending FIs. Caja Trujillo was one of 14 municipally-owned
Table 6: Portfolio composition by lender type

<table>
<thead>
<tr>
<th></th>
<th>Commercial Banks</th>
<th>Municipal Cajas</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Value (USD 1,000)</td>
<td>% of Total</td>
</tr>
<tr>
<td>Commercial</td>
<td>9,549,486</td>
<td>77</td>
</tr>
<tr>
<td>MSME</td>
<td>421,651</td>
<td>3</td>
</tr>
<tr>
<td>Consumption</td>
<td>1,334,091</td>
<td>11</td>
</tr>
<tr>
<td>Mortgage</td>
<td>1,089,131</td>
<td>9</td>
</tr>
<tr>
<td>Total</td>
<td>12,394,358</td>
<td>205,730</td>
</tr>
</tbody>
</table>

Source: Commercial loans account for lending to firms with total debt of at least USD 20,000; micro, small, and medium enterprises (MSMEs) loans apply to firms with debt up to USD 20,000.

cajas in Peru in the late 1990s. The municipal cajas follow a lending model that includes intensively collecting soft information through ongoing visits to clients’ businesses and homes (Jaramillo, 2013). As shown in Table 6, in January 2001, lending to MSMEs and households comprised 88% of total lending from municipal cajas. Excluding commercial banks, Caja Trujillo provided 61% of all credit from regulated FIs in La Libertad.

Figure 8 tracks Caja Trujillo’s performance before, during, and after El Niño. The graphs in this figure are overlayed with a gray box, beginning in July 1997, marking the initial effects of El Niño. This box extends until September 1999; in October 1999 the caja implemented a more aggressive strategy discussed below, signaling recovery. The local economy and the caja have grown rapidly in the past two decades; the caja’s loan portfolio grew from USD 9 million in January 1997 to USD 420 million in December 2013.

While not affecting Caja Trujillo’s portfolio, a nonrepayment crisis occurred among several of its peers driving the average default for the system of municipal cajas from 3% in January 1994 to 30% in August 1994. As a result, it is perhaps unsurprising that at the beginning of 1996, the capital ratio for Caja Trujillo was 32%, signaling its perception of large credit risk.

In the first half of 1997, forecasts of an impending event emerged, leading the government of Peru in June to encourage the public to prepare for a likely severe event. Orlove et al. (2004) surveyed individuals in the Peruvian fishing sector, finding that 39% had received El Niño forecasts before June 1997. During this time, the caja increased its capital ratio from 33% in December 1996 to 43% in July 1997, through reduced lending, a contraction of about 12% of the December 1996 value.

Poor loan performance began in the second half of 1997, as the graph of loan loss provisioning shows. Credit managers attribute repayment problems to higher air temperatures associated with the impending El Niño (see McKay et al., 2003), which affected agricultural commodities such as mangoes. The most devastating consequences of the event occurred due to the torrential rains and ensuing flooding from January to April 1998. Caja Trujillo reported losses from January to March 1998, as shown in the graph of return on assets (ROA). The caja began actively managing problem loans as severe rains emerged in January 1998, restructuring approximately 7% of the portfolio by March 1999. While restructuring reduced revenues, it also allowed the caja to delay (and likely reduce) its realization of losses.

Given the repayment problems recently experienced by its peers and the devastation of El
Figure 8: Financial Performance of Caja Trujillo during the 1998 El Niño

Note: El Niño damaged portfolio quality, reducing income and equity and leading to some credit contraction; however, the caja’s substantial capital reserves and the significant income opportunities in local credit markets facilitated recovery. ROA is in annualized values. Interest income is a percent of the net value of loans (loans minus loan provisioning).

El Niño, Caja Trujillo took a conservative capital management approach as its loan loss provisions continued to grow. Following the event, the data show a credit contraction occurs from December 1998 to January 1999, which coincides with the primary planting season in the region one year after the event. During this second period, the portfolio contracted by 6.4%. This reduction in
lending increased the capital ratio by about 6 percentage points to 49% in the first half of 1999. Provisioning peaked in March 1999, over a year and a half after the event began. By October 1999, the lender’s concerns regarding the extent of losses seems to have dissipated. In October alone, Caja Trujillo expanded its portfolio by 12%, signaling a new strategy: leverage excess capital to grow into recovery. Expanding credit reduced the drag of El Niño-affected loans on portfolio quality. Throughout the event and recovery the lender did not receive external capital, but instead made a large dividend payment in August 1997 as El Niño emerged.

The performance of Caja Trujillo suggests that capital management reduced loan allocations before, during, and after the event. As the graph of loan growth shows, the caja’s portfolio fluctuated, growing and contracting at several points during the event and recovery. The caja reduced lending not in order to stay above minimum regulatory requirements, but due to internal capital targets, and these internal targets changed, growing as El Niño related loss provisions grew and falling after provisions stabilized.

In contrast, commercial banks in the region expanded credit to their borrowers by as much as 30% roughly two months after the torrential rains ended in April 1998. In La Libertad, credit from commercial banks increased by 25% to meet the demand of large firms. This increased credit gap remained until approximately May 1999, roughly a year after the torrential rains ended. For both commercial banks and MSME lenders in northern Peru, I examine lending revenues on performing loans before and after the disaster and find no systematic changes, suggesting that average interest rates did not increased due to a demand shock. This event seemed to create quantity, not price changes in credit markets.

C. MSME panel: Supporting material

The econometric results from Section 5 support the hypothesis of the paper that capital constraints reduce lending following natural disasters. This section considers three alternative explanations for the econometric results. In total, the analyses here are consistent with the interpretation in Section 5; however, they also suggest important differences across contexts that are relevant for future research. Additionally, I assess for dynamic panel bias and the influence of potential violations of strict exogeneity by comparing the first difference model used with a GMM linear panel estimation. These model results are similar and so I conclude the first difference model is suitable.

Alternative hypothesis 1: Credit contraction for lenders with low capital ratios is explained by systematic differences between large and small lenders. Lenders with lower capital ratios tend to be larger (Berger and Bouwman, 2013) and have smoother income (Hughes and Mester, 2013). MSME lenders with lower capital ratios in this sample are larger, but do not necessarily have smoother income, shown in Table 7. Larger lenders also experience less capital market frictions (Portes and Rey, 2005), though whether access to capital markets substantially differs across lenders in this sample is unclear. Thus, lenders with low capital ratios are systematically different from those with high capital lenders; however, the theoretical model in Section 3 predicts that size would lead in the opposite direction of the identified effect: larger lenders with more diversified returns and better access to capital markets are less likely to contract credit following a disaster.
Lender size (Assets) was included as a control in Section 5; however, to explicitly test whether size explains the results, I divide the sample at the median based on portfolio size and replicate the econometric model separately for the larger and smaller lenders in the sample. Results are shown in Table 8 and suggest that capital constraints reduce lending following disasters for both the larger and smaller lenders in the sample, with more immediate and slightly larger effects for low capital lenders that are larger.

*Alternative hypothesis 2: Credit contraction for lenders with low capital ratios is explained by systematic differences between lenders that serve larger and smaller borrowers.* Lenders with low capital ratios may serve a different market segment than highly capitalized lenders and so heterogeneous changes in credit demand across classes of borrowers might explain differences in lending following a disaster between low and high capital lenders. Heterogeneity in borrower demand across market segments could be due to differences in 1) vulnerability to disasters, and/or 2) access to alternative credit. Larger lenders have been found to work with larger, more established and transparent firms that have better access to alternative financing sources (Petersen and Rajan, 2002; Khwaja and Mian, 2008). Lenders with lower capital ratios provide larger loans per borrower in this sample (Table 7), though whether the magnitude of the difference is meaningful is unclear. In the Federal Reserve Bank of New York (2014) survey on Hurricane Sandy, the likelihood of SMES being negatively by the event was unrelated to firm size but positively related to firm age. Perhaps larger SMEs are more likely to receive loans from government programs following a disaster; however, Beck et al. (2010) find that government-supported MSME lending programs tend to be partial guarantees of private sector loans and so would seem to facilitate rather than compete with private sector lending.

To test whether differences in borrower size explains the results, I divide the sample and replicate the econometric model separately for lenders with smaller and larger average loan sizes. Table 8 provides the results and shows that capital constraints reduce lending following disasters in both cases.

Table 7: Capital ratio terciles

<table>
<thead>
<tr>
<th>Loan portfolio (USD)</th>
<th>1st tercile</th>
<th>2nd tercile</th>
<th>3rd tercile</th>
</tr>
</thead>
<tbody>
<tr>
<td>ROA, coefficient of variation</td>
<td>0.95</td>
<td>1.03</td>
<td>0.57</td>
</tr>
<tr>
<td>Avg. loan per borrower (USD)</td>
<td>1026</td>
<td>460</td>
<td>399</td>
</tr>
<tr>
<td>Regulatory Quality</td>
<td>-.30</td>
<td>-.22</td>
<td>-.13</td>
</tr>
<tr>
<td>HDI</td>
<td>0.65</td>
<td>0.63</td>
<td>0.65</td>
</tr>
</tbody>
</table>

Rows report the median value for each capital ratio tercile. *ROA, coefficient of variation* provides the median of the within standard deviation (lender-specific volatility) divided by the mean for annualized return on assets. Regulatory quality is measured in the World Governance Indicators on a range from -2.5 to +2.5 where larger numbers indicate stronger institutions (with a min and max in this sample of [-1.67,0.95]). The Human Development Index (HDI) values in this sample range from 0.20 to 0.83 with larger values indicating more development.

*Alternative hypothesis 3: Credit contraction for lenders with low capital ratios is explained by systematic differences across countries.* This hypothesis is based on a recognition that less developed
Table 8: First difference models of log(loans), comparing across lender and borrower size

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Aggregated</td>
<td>Smaller lenders</td>
<td>Larger lenders</td>
<td>Smaller avg. borrowers</td>
<td>Larger avg. borrowers</td>
</tr>
<tr>
<td><strong>Capital ratio, 1st tercile</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Disaster severityₜ</td>
<td>-0.773***</td>
<td>-0.585</td>
<td>-0.797**</td>
<td>-0.598**</td>
<td>-0.996***</td>
</tr>
<tr>
<td></td>
<td>(0.283)</td>
<td>(0.381)</td>
<td>(0.333)</td>
<td>(0.278)</td>
<td>(0.347)</td>
</tr>
<tr>
<td>Disaster severityₜ₋₁</td>
<td>-0.748***</td>
<td>-0.826***</td>
<td>-0.571***</td>
<td>-0.962***</td>
<td>-0.466***</td>
</tr>
<tr>
<td></td>
<td>(0.144)</td>
<td>(0.224)</td>
<td>(0.185)</td>
<td>(0.184)</td>
<td>(0.133)</td>
</tr>
<tr>
<td><strong>Capital ratio, 2nd tercile</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Disaster severityₜ</td>
<td>-0.0535</td>
<td>0.180</td>
<td>-0.154</td>
<td>0.136</td>
<td>-0.171</td>
</tr>
<tr>
<td></td>
<td>(0.237)</td>
<td>(0.282)</td>
<td>(0.331)</td>
<td>(0.272)</td>
<td>(0.332)</td>
</tr>
<tr>
<td>Disaster severityₜ₋₁</td>
<td>-0.500***</td>
<td>-0.451*</td>
<td>-0.492***</td>
<td>-0.313**</td>
<td>-0.624***</td>
</tr>
<tr>
<td></td>
<td>(0.141)</td>
<td>(0.269)</td>
<td>(0.120)</td>
<td>(0.151)</td>
<td>(0.199)</td>
</tr>
<tr>
<td><strong>Capital ratio, 3rd tercile</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
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</tr>
<tr>
<td>Disaster severityₜ</td>
<td>0.0327</td>
<td>-0.0346</td>
<td>0.221</td>
<td>0.230</td>
<td>-0.150</td>
</tr>
<tr>
<td></td>
<td>(0.334)</td>
<td>(0.310)</td>
<td>(0.482)</td>
<td>(0.476)</td>
<td>(0.290)</td>
</tr>
<tr>
<td>Disaster severityₜ₋₁</td>
<td>-0.0472</td>
<td>-0.192</td>
<td>0.359</td>
<td>-0.0385</td>
<td>-0.139</td>
</tr>
<tr>
<td></td>
<td>(0.162)</td>
<td>(0.191)</td>
<td>(0.256)</td>
<td>(0.354)</td>
<td>(0.147)</td>
</tr>
</tbody>
</table>

Observations 1321 664 657 652 669
Adjusted $R^2$ 0.251 0.179 0.336 0.277 0.265

Standard errors in parentheses
* p<.10, ** p<.05, *** p<.01

The first column uses all observations and replicates the regression in Table 5. Please see that table for additional specification details, which are consistent across all models here. The remaining columns divide the sample at the median. The second and third columns replicate the model for lenders above and below median loan portfolio size. Smaller versus larger average borrowers divide the sample at the median using average loan size per borrower.

countries are generally more vulnerable to disasters (Noy, 2009) and have weaker public institutions. Thus, lenders in less developed countries may operate with lower capital ratios and experience greater economic disruptions, which could explain why lenders with lower capital ratios lend less following a disaster. Table 7 shows that regulatory quality is lower for lenders with low capital ratios but differs little across levels of development as measured by the United Nations Human Development Index (HDI).

The disaster measure, the proportion of the population affected by a disaster each year, shows greater differences across time than across countries (within variance of 0.0039, between variance of 0.0008). To account for the influence of unmeasured country conditions, I estimate a first difference model with country fixed effects. Because the time series is relatively short, country fixed effects may be biased by large shocks. As a result, I use them exclusively in this regression for comparison. The results of this model, shown in Column 2 of Table 9, are consistent with the qualitative results of the main model (including the same statistically significant variables) but do reduce the magnitudes of the significant coefficients. Thus, the results are not explained by differences across countries, but country context does seem to matter.

The results in Table 9 indicate that the consequences of disasters on lending are greater in the more developed countries in the sample. They indicate that for countries either with high regulatory quality or HDI, disasters result in a significant reduction in lending across levels of

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9All countries in the sample are considered developing and emerging. The country with the highest HDI score is Hungary, which is ranked 69th in the world.
capital but that this effect is greatest and most persistent for the least capitalized lenders. Lenders in countries with lower regulatory quality are more likely to reduce lending in the period following a disaster, which is perhaps due to less stringent enforcement of how/when lenders report losses.

Table 9: First difference models of log(loans), comparing across country development

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Aggregated</td>
<td>Aggregated</td>
<td>Low regulatory</td>
<td>High regulatory</td>
<td>Low HDI</td>
<td>High HDI</td>
</tr>
<tr>
<td>Capital ratio, 1st tercile</td>
<td></td>
<td></td>
<td>quality</td>
<td>quality</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Disaster severity_t</td>
<td>-0.773***</td>
<td>-0.668**</td>
<td>-0.715**</td>
<td>-1.264***</td>
<td>-0.592**</td>
<td>-1.425***</td>
</tr>
<tr>
<td></td>
<td>(0.283)</td>
<td>(0.292)</td>
<td>(0.348)</td>
<td>(0.235)</td>
<td>(0.281)</td>
<td>(0.268)</td>
</tr>
<tr>
<td>Disaster severity_t−1</td>
<td>-0.748***</td>
<td>-0.593***</td>
<td>-0.890***</td>
<td>-0.410*</td>
<td>-0.860***</td>
<td>-0.686***</td>
</tr>
<tr>
<td></td>
<td>(0.144)</td>
<td>(0.168)</td>
<td>(0.216)</td>
<td>(0.224)</td>
<td>(0.209)</td>
<td>(0.207)</td>
</tr>
<tr>
<td>Capital ratio, 2nd tercile</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Disaster severity_t</td>
<td>-0.0535</td>
<td>0.102</td>
<td>-0.0909</td>
<td>-0.623*</td>
<td>-0.0161</td>
<td>-0.580*</td>
</tr>
<tr>
<td></td>
<td>(0.237)</td>
<td>(0.245)</td>
<td>(0.228)</td>
<td>(0.311)</td>
<td>(0.237)</td>
<td>(0.298)</td>
</tr>
<tr>
<td>Disaster severity_t−1</td>
<td>-0.500***</td>
<td>-0.309**</td>
<td>-0.743***</td>
<td>0.244</td>
<td>-0.712***</td>
<td>0.0263</td>
</tr>
<tr>
<td></td>
<td>(0.141)</td>
<td>(0.129)</td>
<td>(0.187)</td>
<td>(0.269)</td>
<td>(0.118)</td>
<td>(0.259)</td>
</tr>
<tr>
<td>Capital ratio, 3rd tercile</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Disaster severity_t</td>
<td>0.0327</td>
<td>0.124</td>
<td>0.349</td>
<td>-1.188***</td>
<td>0.185</td>
<td>-1.015**</td>
</tr>
<tr>
<td></td>
<td>(0.334)</td>
<td>(0.347)</td>
<td>(0.222)</td>
<td>(0.296)</td>
<td>(0.351)</td>
<td>(0.375)</td>
</tr>
<tr>
<td>Disaster severity_t−1</td>
<td>-0.0472</td>
<td>0.135</td>
<td>-0.0277</td>
<td>0.213</td>
<td>-0.0716</td>
<td>0.329</td>
</tr>
<tr>
<td></td>
<td>(0.162)</td>
<td>(0.188)</td>
<td>(0.175)</td>
<td>(0.352)</td>
<td>(0.202)</td>
<td>(0.402)</td>
</tr>
<tr>
<td>Country fixed effects</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td>Observations</td>
<td>1321</td>
<td>1321</td>
<td>696</td>
<td>625</td>
<td>677</td>
<td>644</td>
</tr>
<tr>
<td>Adjusted $R^2$</td>
<td>0.251</td>
<td>0.300</td>
<td>0.300</td>
<td>0.272</td>
<td>0.279</td>
<td>0.259</td>
</tr>
</tbody>
</table>

Standard errors in parentheses
* p<.10, ** p<.05, *** p<.01
The first column uses all observations and replicates the regression in Table 5. Please see that table for additional specification details, which are consistent across all models here. The second column adds country fixed effects. The remaining columns divide the sample at the median. Regulatory quality is a measure provided by the World Governance Indicators. The final columns use the Human Development Index (HDI) as a measure of country development.

GMM linear panel estimation. The models estimated in Section ?? are potentially good contenders for dynamic panel estimation as the sample comprises a large N, small T panel; explanatory variables that may not be strictly exogenous; and a potentially dynamic loan growth process. Complications related to these characteristics may influence model results due to dynamic panel bias and/or violations of strict exogeneity in model estimation so I estimate a generalized method of moments linear panel model in the spirit of Arellano and Bond (1991). Table 10 reports in Column 1 the model results from the first difference model in Section ?? for comparison. Column 2 provides the difference GMM. The model uses two-step estimation and the standard errors correction from Windmeijer (2005). The table footnote describes the model instruments. The specification passes the Hansen test for overidentifying restrictions and the Arellano-Bond test for autocorrelation in first-differenced errors. The difference GMM estimation provides qualitatively the same results as the first difference estimator, though the current period estimate of the effect of disasters on loan growth for the lowest capital lenders is much larger. The results support the main findings and suggest that panel bias and endogeneity are not driving the main econometric results.

Table 10: First difference and difference GMM models of log(loans)

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Capital ratio, 1st tercile</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Disaster severity&lt;sub&gt;t&lt;/sub&gt;</td>
<td>−0.757*** (0.251)</td>
<td>−2.359*** (0.854)</td>
</tr>
<tr>
<td>Disaster severity&lt;sub&gt;t−1&lt;/sub&gt;</td>
<td>−0.734*** (0.168)</td>
<td>−0.586** (0.267)</td>
</tr>
<tr>
<td><strong>Capital ratio, 2nd tercile</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Disaster severity&lt;sub&gt;t&lt;/sub&gt;</td>
<td>−0.134 (0.232)</td>
<td>−0.898** (0.449)</td>
</tr>
<tr>
<td>Disaster severity&lt;sub&gt;t−1&lt;/sub&gt;</td>
<td>−0.533*** (0.145)</td>
<td>−0.527 (0.354)</td>
</tr>
<tr>
<td><strong>Capital ratio, 3rd tercile</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Disaster severity&lt;sub&gt;t&lt;/sub&gt;</td>
<td>0.0563 (0.350)</td>
<td>−0.546 (0.518)</td>
</tr>
<tr>
<td>Disaster severity&lt;sub&gt;t−1&lt;/sub&gt;</td>
<td>0.110 (0.145)</td>
<td>−0.133 (0.230)</td>
</tr>
</tbody>
</table>

Observations 1321 1608  
Number of groups 607  
Number of instruments 106  
Adjusted $R^2$ 0.246  
Arellano-Bond AR(1) test (p-value) 0.000**  
Arellano-Bond AR(2) test (p-value) 0.637  
Hansen test (p-value) 0.720  

Standard errors in parentheses  
* p<.10, ** p<.05, *** p<.01

Models of log(loans). The outcome variable is the total value of the MSME lender’s outstanding loan portfolio before accounting for write-downs in loan value due to poor performance. Column 1 repeats first difference estimation results from Table 5 for comparison; please refer to that table for specification details. Column 2 uses the first-differenced GMM linear panel estimator proposed by (Arellano and Bond, 1991). It employs two-step estimation, the standard errors correction proposed by Windmeijer (2005), and year fixed effects. The model also includes the following explanatory variables: a one-period lag of log(loans) and contemporaneous values of lender write-off, capital, and liquidity ratios; log(GDP per capita); inflation; regulatory quality; political stability; and accountability. I created GMM-style instruments for the first-period lag of log(loans), the capital-disaster interactions terms, and lender write-off, capital, and liquidity ratios, using lags 2 and greater for each and “collapsing” the instrument matrix (e.g., as discussed by Roodman, 2009). Log(GDP per capita), inflation, regulatory quality, political stability, and accountability are included as standard instruments.


**URL:** www.emdat.be


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