

Natural Disasters, Credit Supply, and Insurance

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Abstract

Natural disasters exacerbate credit supply constraints in informationally opaque markets such as those for micro, small, and medium enterprises (MSMEs). To serve these markets, lenders rely on soft information that motivates geographic concentration, increases capital market frictions, and complicates regulatory supervision. I formalize this framework in a dynamic model to examine lender behavior under risk. Risk motivates the modeled lender to hold a capital buffer above minimum requirements, reducing credit supply. Moreover, disasters lead to large loan losses that cause the lender to contract credit after the event, slowing recovery for the affected economy. The behavior of a regionally important MSME lender in Peru during severe El Niño-related flooding is consistent with modeled results. In contrast, commercial banks increased lending to their clients, which tended to be large firms. Finally, this paper extends the model to test a contingent claims contract that makes payments based on an observable measure of El Niño and is currently being sold in Peru. Such products seems ideally suited for opaque lenders managing portfolios with disaster concentrations.

Keywords: natural disasters, credit supply shocks, incomplete information, capital market frictions

1. Introduction

This paper explores supply side credit constraints created by natural disaster risk in an emerging economy where financial markets are underdeveloped. Despite the importance of this topic, to my knowledge this is the first paper with a primary objective of understanding these supply side constraints. I propose a framework that explains the challenge of natural disaster risk for micro, small, and medium enterprise (MSME) finance as a consequence of the information problems previously documented in these markets. Lending to opaque borrowers motivates geographic specialization, which increases systemic exposure to spatially correlated disasters. Moreover, lending to opaque borrowers creates opaque lenders, reducing access to capital markets. Natural disasters increase asymmetric information and so exacerbate capital market frictions following a severe event. Lender opacity also complicates supervision, increasing the importance of capital as an observable indicator of loss capacity.

The paper formalizes the proposed framework in a dynamic, partial equilibrium model to examine lender behavior. 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, incurs increasing information costs of expanding its portfolio, and is supervised based on its capital ratio. Disasters create loan losses that lower its 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 regulatory requirements, which has the effect of reducing the credit supply in non-disaster conditions. Implications of the modeled results are troubling given that credit constraints are frequently high in MSME markets and that disasters tend to increase credit demand for recovery and rebuilding.

The paper compares these results to the experience of an important MSME lender in the affected region of Peru during the 1998 El Niño. While some modeling assumptions used for tractability do not hold, capital management seems to drive credit contraction following the severe event. Moreover, this lender maintained a very high capital ratio (over 40%), suggesting a large perceived vulnerability to systemic risk. In contrast to the contraction of MSME credit markets, large banks expanded credit in affected regions by reallocating capital internally to meet the increased demand of their clients, which were primarily large firms.

Finally, the paper discusses disaster-contingent claims as a means to address the credit supply problems created by natural disasters. I model both a formal insurance contract used by an independent MSME lender as well as an internal contingent claims market in a bank holding company, a contract between a vulnerable subsidiary and its parent. The modeled contracts are based on El Niño insurance, a product now available in Peru that is a parametric mechanism which bases payments solely on an objective measure of disaster severity. Such a mechanism allows lenders to manage their (unobserved) portfolio concentrations of disaster risk using this observable index of the disaster. The model results indicate that disaster-contingent claims can greatly reduce credit supply shocks and expand access to credit in these underdeveloped markets.

1.1. Motivation and framework

Natural disaster risk is rising due to a confluence of events including increased development and urbanization, population growth, and more volatile weather (Kunreuther and Michel-Kerjan, 2009; Samson et al., 2011; Stern, 2008). In 2012, Munich Re (2013) estimates losses of \$170 billion and 9,600 fatalities from natural disasters. 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, this report cites evidence that current temperature and rainfall extremes have already increased relative to 1950. The world is growing riskier.

Recent macroeconomic evidence highlights 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 – following neoclassical growth models, as the absolute level of physical capital falls its marginal product rises. As a result, the net economic impact of a disaster is significantly affected by the ability of an economy to mobilize reinvestment. 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 private firms may be particularly important for facilitating recovery.

This paper focuses on some of the market segments for which lending remains most difficult: small and medium enterprises (SMEs), especially agricultural producers, and the poor, which I collectively call MSMEs hereafter. The paper also emphasizes developing and emerging economies where developmental barriers have delayed the implementation of technological advancements that have reduced credit constraints in developed countries. Still, while not the direct focus, the findings are also relevant to developed economies. For example, despite strong social safety nets in the U.S., its Small Business Administration SBA (2013) reports that 25% of firms permanently fail following a major disaster.

The steps lenders take to serve MSME markets make them more vulnerable to natural disasters. Academic research on credit markets and disaster risk remains nascent so I begin by borrowing from other subfields of the financial intermediation literature, proposing a framework to explain why natural disasters are likely to be so onerous for MSME lenders. This framework is based on four well-documented findings: 1) MSMEs tend to be informationally opaque and vulnerable to significant risk; 2) lending to MSMEs motivates 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.

1.1.1. 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; Headd, 2003; Pompe and Bilderbeek, 2005; Wiklund et al., 2010). Each of the groups profiled here, agricultural producers, small and medium enterprises, and the poor are also quite vulnerable to natural disasters. Agricultural vulnerability to climatic risk is clear. SMEs tend to be at greater risk than larger firms because they are often more specialized, are less likely to plan for infrequent events, and have fewer financial resources (Tierney, 1997; Wasileski et al., 2011). 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).

Problems of imperfect information are a hallmark of lending (Stiglitz and Weiss, 1981), and MSMEs tend to have some of the greatest informational barriers. Despite advances in informational and financial technologies that have increased hard, quantifiable data on these firms (Berger and Udell, 2006; DeYoung et al., 2004; Petersen and Rajan, 2002), lending constraints due to opacity often remains high 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; DeYoung et al., 2004; Petersen and Rajan, 2002), and the poor (Armendáriz and Morduch, 2011; Behr et al., 2011). For example, 43% of small

enterprises in developing countries and 17% in developed countries cite access to credit as a major operational obstacle (G20 Financial Inclusion Experts Group, 2010).

1.1.2. Reducing asymmetries through geographic specialization

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). 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).

This lending approach results in a mutually vested interest among FIs and MSMEs (Agarwal and Hauswald, 2010; Berg and Schrader, 2009). Lenders holding private information on local firms capture market rents through monopolistic pricing and so benefit from the success of these firms. Their borrowers face switching costs in the form of educating a new lender so also benefit from their lender's success as it protects their access to credit.

1.1.3. 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). Indeed, 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 instruments 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 \$2 billion in 2005 to \$25 billion in 2011 (CGAP, 2012). Yet, these investors are primarily holding fixed income instruments with only about 20% of total investments in equity and those are in the largest, most secure MSME lenders (MicroRate, 2011; Symbiotics, 2013).

In the presence of capital market frictions, FIs incurring large loan losses that reduce capital to unacceptable levels must realign their balance sheets by reducing the size of its assets and liabilities (Peek and Rosengren, 1995). Thus, FIs experiencing a low capital ratio will tend to originate fewer new loans, relying on retained earnings to replenish their capital base but also slowing recovery and leading to foregone profits (Houston et al., 1997; Van den Heuvel, 2009).

1.1.4. Supervision under opacity

Regulatory supervision of MSME lenders is also constrained by asymmetric information (e.g., see Boot and Thakor, 1993; Tirole, 1986).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 at the end of 2010. 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). Almost without exception and due in part to the information problem, MSME lenders determine their regulatory capital based on the simplest approaches in the Accords (the Standardized Approach for credit risk) in which all SME loans are provided the same risk weight (BCBS, 2006, 2010, 2011).²

In this context, regulatory capital is not a reflection of economic capital, but a mechanism that allows supervisors to commit to intervening based on 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

¹Cross-country evaluations of regulatory supervision suggest that one of its most beneficial aspects is increasing accurate information disclosure among FIs (Barth et al., 2004; Beck et al., 2006).

²Effectively, MSME lenders in developing and emerging economies are still operating under Basel I style requirements, which Greenspan (1998) notes do not encourage diversification, hedging, or other portfolio risk mitigating approaches.

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, [United States 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, holding capital buffers in excess of minimum requirements based on portfolio risk. Still, revealed risk through excess capital buffers provides a second-best outcome due to the information problem because it increases the consequences of capital market frictions.

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

Bank holding companies represent a stark 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 so that even if large banks included both opaque and transparent subsidiaries, effective internal capital markets are only likely to function for the 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.

1.1.6. Summary and implications for credit markets vulnerable to natural disasters

When combined, the above literatures paint a challenging image of MSME lending under disaster risk. These conditions suggest a fragility potentially leading to credit market breakdown when disasters occur. The geographic concentrations that enable lenders to overcome imperfect information and reach these clients can quickly lead to systemic banking losses because entire communities and regions are adversely affected by the same event. Disaster losses increase demand for credit among firms and capital among lenders; however, these losses also exacerbate the information problems at both levels as past performance may no longer predict current performance. Without access to external capital, local lenders may be poorly equipped to address increasing demand. Opaque borrowers whose soft information is held in this lender may be unable to demonstrate their creditworthiness to other sources, delaying local investment and disaster recovery. Given this proposed framework, it is perhaps unsurprising that lenders avoid or ration credit in communities and sectors that are highly vulnerable to disasters ([Binswanger and Rosenzweig, 1986](#); [Boucher et al., 2008](#); [Hoff and Stiglitz, 1990](#)).

1.2. Previous research on natural disasters and credit dynamics

A handful of papers explore the consequences of natural disasters on credit markets. The most systematic research thus far has focused on access to and demand for credit after a disaster among households and opaque firms and is consistent with the framework 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.

[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 (e.g., inundated assets) from the flood, but also those not directly affected, seemingly due to higher food prices and reduced income resulting from labor market disruptions.

[Berg and Schrader \(2012, 2009\)](#) study the effects of volcanic eruptions on credit access for opaque firms in Ecuador. They use individual loan data provided by ProCredit, a multinational bank holding company

specialized in MSME lending.³ Berg and Schrader (2012) find that the number of credit applications increased following volcanic activity. They also find important differences in loan approval based on whether firms had a previous relationship with the lender. Firms that had never borrowed from ProCredit were significantly less likely to be approved for a loan after a volcanic event; however, approval rates were unaffected for previous borrowers. Additionally, Berg and Schrader (2009) find that volcanic activity increases MSME credit risk. First-time borrowers experienced higher default rates following the disaster. Repeat borrowers were given lower interest rates during the recovery period, which seemed to offset their increased risk as their default rates remained constant. Interestingly, Berg and Schrader (2009) find that repeat borrowers pay higher interest rates than new borrowers during nonemergency conditions. These results suggest that repeat borrowers are paying for an implicit option unavailable to first-time borrowers, access to liquidity at low interest rates in the event of a disaster.

While not studying a natural disaster, Khwaja and Mian (2008) also highlight the limited ability of opaque borrowers to find a new lender during a banking crisis. Following its nuclear tests in 1998, the government of Pakistan imposed restrictions on dollar-denominated deposits, most greatly affecting large domestic banks. This policy disrupted access to credit with dollarized banks lending less than those holding Pakistani rupees. Large firms responded by finding credit at less affected banks; however, smaller firms were generally unable to manage this transition and so borrowed less. As a result, these small firms were more likely to enter financial distress following the nuclear tests.

My research contributes by directly examining the implications for credit supply of lender behavior under disaster-related credit risk – to my knowledge the first paper to directly examine this topic in detail. While some studies have documented supply-side challenges of natural disasters, in almost every case, its treatment has been cursory and ancillary to the core research objectives. For example, economic history from the U.S. identifies climate as an exacerbating factor in bank failures, but the generalizability of those events is unclear given the unusual historical context. In the postbellum U.S., adverse weather via cotton losses caused national economic downturns and systemic bank failures (e.g, see Davis et al., 2009; Hanes and Rhode, 2012; Kupiec and Ramirez, 2012). The vulnerability of the entire U.S. economy to regional adverse weather was due to a confluence of factors pertaining to the international gold standard and cotton production and export. Still, evidence from this time shows a mutually causal linkage between bank failure and farm failure (Kupiec and Ramirez, 2012).

In the 1920s, over 80% of bank failures in the U.S. were in farming regions where small banks predominated rural communities Alston et al. (1994). Alston et al. (1994) argues that overindebtedness developing from a period of unsustainably high agricultural prices and flawed public policies such as states' first attempts at deposit insurance created weakness in the banking system. As a result, geographic and sectoral concentrations led banks to fail when farm income declined due to unfavorable prices and/or weather.

Hosono et al. (2012) study SME investment following the Kobe earthquake in 1995. Firms in damaged areas had higher investment ratios, presumably because they experienced a higher marginal product of capital. 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, suggesting that firm production was adversely affected by credit supply constraints. Also, firms that borrowed from small banks or credit cooperatives had, on average, investment ratios 10 percentage points lower than those borrowing from larger banks; however, the authors do not directly control for SME opacity so selection bias may account for the differences between the clients of small and large banks.

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 drought periods 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.

My research is most similar to Collier and Skees (2012) who present a banking model to estimate the consequences of severe El Niño for vulnerable microfinance intermediaries. Their model is an Excel-based, risk-planning educational tool which they developed to assist lenders and other vulnerable decision makers

³ProCredit's social mission motivates them to serve opaque clients but operate hierarchically, a model that Stein (2002) and others predict reduces efficiency. For more information on their approach, please visit <http://www.procredit-holding.com/>.

in evaluating El Niño insurance. The model developed and presented here confirms some of their results such as credit supply interruptions following a severe event, but also extends their work in several important ways. First, I provide a framework for understanding why managing natural disasters through diversification and external capital markets may be infeasible for many lenders. Second, while their model is embedded in an Excel file and difficult to evaluate, I provide a formal, tractable, dynamic economic model that enhances evaluation and interpretation of its mechanics and results. Third, my model allows for evaluation of optimal lender behavior under risk, something not possible in the Collier-Skees model.

1.3. Formalizing the framework

This section formalizes the framework presented in Section 1.1 in a dynamic, rational expectations model to examine lender behavior. It is a partial equilibrium, supply side model, assuming inexhaustible (i.e., infinitely elastic) demand at the lending interest rate. While theory predicts that the increased demand for credit after a disaster would increase interest rates, the limited available empirical evidence (e.g., [Berg and Schrader, 2009](#)) suggests that lenders do not increase rates following a disaster. I find no evidence of increasing interest rates in MSME markets in Peru following the 1998 El Niño. Such behavior could be explained in several ways including 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).

Because lenders serving opaque borrowers exercise market power ([Agarwal and Hauswald, 2010](#)), these rents allow MSME lenders to continue to grow, challenge dynamic models because model state variables do not converge in absolute terms. While several approaches can solve this problem, model stationarity is achieved here by treating the lending interest rate as given, as described in the previous paragraph and discussed further in Section 2.

Dividends are modeled as a given fraction of equity each period, which may surprise some readers who expect that shareholders are not likely to require a dividend during and immediately following a disaster. This approach removes the effect of implicit disaster risk transfer from the model results. Section 4 discusses disaster-contingent claims, and dividends paid as a function of disaster occurrence is a specific example of that more general discussion.

Regulating supervisors may intervene with undercapitalized lenders using a variety of strategies that entail financial (preventing certain types of lending) and/or non-financial but stigmatic (requiring a recovery plan, publicly reporting noncompliance) implications. The primary focus here is modeling the effects of disasters on lenders; therefore, to avoid confounding the financial consequences of a disaster from those of regulatory intervention, regulatory intervention is modeled exclusively as a stigma – regulatory penalties reduce the lender’s welfare but do not impose financial penalties.

Finally, this model focuses on credit risk and lender capital and ignores disaster-related liquidity risk. Disasters may also create liquidity shocks as depositors withdraw funds to manage their needs and borrowers fail to repay loans. Moreover, asymmetric information can also constrain access to debt financing (e.g., see [Holod and Peek, 2007](#)). This paper focuses on equity capital and credit risk and leaves liquidity risk for future research because [Diamond \(1984\)](#) demonstrates that information problems are more consequential for equity than debt financing.

1.3.1. Model

A risk-neutral lender attempts to maximize its stream of dividend payments over an infinite horizon. This lender manages a stock of equity capital K and is unable to attract additional equity investments. Each period, the lender begins with a portfolio of one-period loans L that are about to mature and so determines to originate new loans l at a given interest rate r . Lending is exposed to the production risks of borrowers including that associated with a large natural disaster, leading to an exogenous, random nonrepayment rate $\xi \in [0, 1]$. Thus, the level of outstanding loans that transfer to the next period is

$$L' = (1 - \xi)l. \tag{1}$$

Let d be the residual between loans and equity, $d = l - K$. Typically, d is positive; the lender chooses to lend more than its current equity and finances this decision at rate r^d . Instead, d can be negative; in which case the lender holds its un-lent equity in other FIs and earns r^d .

Additionally, the lender incurs information and origination costs $h(l)$ associated with finding, evaluating, and monitoring borrowers. Because of the limited supply of good borrowers, these information and origination

costs grow at an increasing rate, $h' > 0, h'' > 0$. Finally, the lender adjusts its value based on loan losses ξl . Thus, its income function is

$$\pi = (1 - \xi)rl - r^d d - h(l) - \xi l. \quad (2)$$

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

$$K' = (1 - \nu)K + \pi \quad (3)$$

where ν is the dividend rate.

The regulating supervisor monitors the lender by its capital ratio K/L . If the lender's capital ratio falls below the regulated minimum κ , the supervisor responds with increasingly invasive interventions that the lender finds undesirable. This penalty is represented as

$$g(K, L) = \gamma \max\{0, \kappa - K/L\}^2 L$$

such that shortfalls are punished at an increasing rate.

Given these conditions, the lender's problem is

$$V(K, L) = \max_{l \geq 0} \{vK - g + \delta E_\xi [V(K', L')]\} \quad (4)$$

1.3.2. Deterministic model results

The model structure limits describing its mechanics analytically; however, the deterministic version provides some useful insights. Let $\bar{\xi} = E[\xi]$. The first order conditions for the deterministic model are

$$V_l : V_{K'}((1 - \bar{\xi})r - r^d - h_l - \bar{\xi}) + V_{L'}(1 - \bar{\xi}) \leq \mu \quad (5)$$

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

$$V_K : \nu - g_K + \delta(1 - \nu + r^d)E[V_{K'}] = V_K$$

$$V_L : -g_L = V_L.$$

Assuming an interior solution, (5) leads to an optimal lending policy that equates

$$r(1 - \bar{\xi}) - r^d - \bar{\xi} = h_l - g_L \frac{1 - \bar{\xi}}{\lambda}. \quad (6)$$

where $\lambda = V_{K'}$ is the shadow price of capital. On the left hand side, the financial margin $r(1 - \bar{\xi}) - r^d$ and loan losses $\bar{\xi}$ are linear in loans; on the right hand side, origination and information costs and regulatory penalties are convex. For a given level of equity, information and regulatory costs limit loan origination.

At the steady state, (3) identifies that

$$K^* = (1 - \nu)K^* + \pi \implies \pi = \nu K^*. \quad (7)$$

The size of the lender is set at the point where income equals the cost of equity capital, the dividend rate.

2. Methods

This section describes model calibration and the numerical solution techniques used to solve the model. Model calibration is based on the risk of El Niño related flooding and its effects on MSME lending in northern Peru. Through several projects, I conducted field work in Peru, as part of a team studying the consequences of El Niño risk for credit markets and advising an emerging risk transfer market attempting to address El Niño.⁴ The model is calibrated for one of several FIs with whom we collaborated in risk assessment and stress-test modeling. This section draws on three sources of hard data: 1) financial data (e.g., income statements and balance sheets) available from the Peruvian banking regulator's website,⁵ 2) a survey we conducted jointly with the modeled lender assessing its El Niño-related credit risk, and 3) ocean temperatures used to model El Niño severity from the U.S. National Oceanic and Atmospheric Administration (NOAA). Table 1 summarizes calibration values, which are discussed below. We learned a great deal through extensive conversations with many FIs in Peru (MSME lenders, commercial banks, cooperatives, etc.) from which I selectively draw in discussing the hard data used here and in Section 3.

⁴That team was led by Dr. Jerry Skees and the work funded by the Bill & Melinda Gates Foundation, the United Nations Development Programme, and GIZ, a German consultancy.

⁵sbs.gob.pe

2.1. Probability of severe El Niño

Severe El Niño events are the result of a disruption in ocean and atmospheric circulation along the equatorial Pacific. This disruption increases the Pacific surface temperature, creating convection. As this warm, moist air moves east, it meets the cool air descending from the Andes, resulting 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 occurred in 1998; the previous severe event was in 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 to estimate the probability of a severe event. Moreover, elevated ocean temperatures predate severe rains in Peru so that these events are probabilistically forecastable several months in advance. Niño 1+2 is a monthly measure of ocean temperatures near the coast of Peru and Ecuador collected by 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.⁶ The Appendix includes an evaluation of the Niño 1+2 data and the process by which I fit its distribution. Based on those analyses, the annual probability of a severe El Niño is 4.6%.

2.2. Financial intermediary calibration

The FI for which the model is calibrated is a deposit-taking institution with an average loan size of \$1,600 and a credit portfolio of over \$500 million. Its stated mission is to provide financial services to micro and small enterprises with the hope of improving quality of life for lower income people. Ninety five percent of its revenues come from direct lending to non-financial firms and households. Similar to its peers, the FI initially specialized in three regions, one in each southern, central, and northern Peru and has expanded from those regional offices. Its primary shareholder is a Peruvian commercial bank.

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 34.2%, 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%. Financial performance indicators (e.g., return on equity, ROE) are discussed in Section 3.1 in comparison with simulation results.

Dividends. To preserve the high profitability of the (monopolistic) lender in the model, I set an artificially high dividend rate (dividends/equity). In other words, market rents are fully extracted by shareholders. Section 1.3.2 illustrates that the lender’s deterministic steady state distribution is characterized by equating income to dividends. Thus, while the observed dividend rate for this lender is 11%, I set its dividend rate equal to its average ROE during the evaluation period, 32%. This approach models FI performance around the mean of its steady state well. When a disaster occurs and drives the simulated lender away from the steady state mean, however, this approach will overestimate the duration of recovery because earnings that actually would be retained are paid as dividends in the model.

Origination and information costs. Origination and information costs $h(l)$ are calibrated using the administration costs of the modeled FI, assuming the form

$$h(l) = \alpha l + \beta l^2.$$

where α is origination and β is information costs. While empirical evidence suggests that information costs are convex in loans (e.g., Agarwal and Hauswald, 2010), modeling $h(l)$ as quadratic is a stronger assumption that is convenient for the solution technique and does not affect the modeling objective. Administrative costs are not reported as “origination” and “information” costs and so were chosen arbitrarily such that the combination is consistent with observed administrative costs as a percent of loans. Because information costs β are fundamental to determining the size of the lender in absolute terms (as shown in Section 1.3.2), results are presented and discussed in proportions (e.g., loan allocations as a percent of pre-disaster levels) rather than in specific values.

⁶Analyses not shown but available on request from the author.

Table 1: Calibration summary, annualized values

Parameter	Symbol	Value
Lending interest rate	r	34.2%
Borrowing interest rate	r^d	5.1%
Origination expense	α	2.1%
Information expense	β	0.01%
Capital penalty	γ	100
Discount rate	δ	95.75%
Minimum capital requirement	κ	14%
Dividend rate	ν	32.0%
Expected nonrepayment rate (nondisaster)	η	3.0%
Standard deviation of nonrepayment (nondisaster)	σ	0.24%
Disaster nonrepayment	ψ	3.5%
Disaster probability	$P[t \geq 24.5^\circ]$	4.6%
Insurance premium	p	8.05%
Insurance trigger	\bar{t}	24.5°

Regulatory penalty. The parameter γ on the capital penalty is not directly observable as it represents the degree to which the FI considers supervisory intervention undesirable. I set $\gamma = 100$ as an effective illustrative example and discuss alternative specifications in a sensitivity analysis in Section 3.1.3.

Discount rate. The annual discount rate is set using the interbank rate in Peru, which was 4.25% during the evaluation period. Model results are qualitatively insensitive to the discount rate, for which (6) provides some intuition.

2.3. Risk survey and expected losses

El Niño-related loan loss data from Peru are available for a single severe event and at the portfolio level. Moreover, because the last severe event occurred more than 15 years prior to the current risk assessment, the capacity of historical losses to predict current exposure is unclear. As a result, the judgment of risk managers in the modeled MSME lender is used to estimate its current exposure and compare these results to historical loss data.

The FI surveyed its office and credit risk managers regarding their perceived credit exposure to severe El Niño. Roughly 20% of its portfolio is in the region vulnerable to El Niño. The loss estimates for the surveyed FI should be understood as vulnerability given the current risk management strategies of the FI including its capacity to use El Niño forecasts to limit exposure. While lenders follow forecasts, they use them limitedly due to forecast error, ongoing relationships with their clients that make credit rationing difficult, and the inability to recall long-term loans quickly.

Twenty seven participants completed the survey from the vulnerable region. The survey 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 these events:

- “If a similar event occurs as that in 1998, we would certainly have negative consequences for the entire economy, especially because the area we serve depends heavily on the viability of roads. These roads being blocked or interrupted by landslides would affect significantly the normal operations of our commerce and transport clients.”
- “We are concerned by severe El Niño...the city-level infrastructure is unable to prevent flooding because the main channel of the river runs through the city. Also, we have loans in grape production and other export products which are the main source of income for the rural area around the city, including an important source of income for dependent laborers. At the office in Unión, the river floods the farmland, as it has no proper outlet, and the rain affects agricultural products such as cotton, corn, and rice that provide the main income in the area.”
- “As the waters warm from El Niño, the aquatic species and fishing industry will move away from our coastline, leading to a shortage of fish.”

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

The 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%). Combining these estimates with its portfolio allocations indicates that the FI expects to lose 15% of the value of its loan portfolio in the vulnerable regions if a severe El Niño occurs. Aggregating these results to the total portfolio, across regions, the FI expects to lose 3.5% of the value of its outstanding loans from a severe El Niño event.

This estimation seems plausible given the experience of similar lenders during the 1998 event. [Collier et al. \(2011\)](#) estimate loan losses for an MSMSE lender in the region for the 1998 severe El Nio using an event studies methodology, finding that roughly 3.4% of that lender’s portfolio stopped performing based on original loan terms. Also as shown in Section 3.2, loan loss provisions for Caja Trujillo increased by about 6 percentage points due to El Niño. In 2001, the earliest date available, the typical ratio of provisions to write-offs is 2.7. Assuming that this ratio is similar during El Niño, the observed increase in provisions would correspond with approximately 2.2% of the portfolio written off.

2.3.1. Modeling loan losses

The nonrepayment rate is based on the definition of default identified in Basel II, loans past due for more than 90 days. Loan losses $\xi(x, \epsilon)$ are modeled using the following process

$$\xi(x, \epsilon) = \eta + \psi x + \epsilon \quad (8)$$

where η is expected nonrepayment under normal (i.e., non-disaster) conditions, x describes the occurrence and influence of a systemic, natural disaster shock on loan losses, ψ weights this influence based on portfolio concentration, and ϵ is unexplained variation in the realization of loan losses, which is assumed to be $\epsilon \sim N(0, \sigma^2)$. While the systemic shocks might more generally be modeled with a complex functional form, because the data provide a single observation of a severe event, I model the shock as binary, i.e., $x = \{0, 1\}$ and $\psi = 0.035$.

2.4. Solution techniques

The Bellman equation (4) is solved using the method of collocation, which calls for the value function $V(K, L)$ to be approximated using a linear combination of $n \times n$ known basis functions ϕ_{ij} :

$$V(K, L) \approx \sum_{i=1}^n \sum_{j=1}^n z_{ij} \phi_{ij}(K, L).$$

The unknown coefficients z_{ij} are then fixed by requiring the value function approximants to satisfy the Bellman equation (4), not at all levels of equity K and outstanding loans L , but rather at n collocation nodes K_i and L_j . The collocation method replaces the Bellman functional equations with a set of $n \times n$ nonlinear equations with $n \times n$ unknowns that are solved using Newton’s method. The collocation method can generate highly accurate approximate solutions to the Bellman equation, provided the basis functions and collocation nodes are chosen judiciously and their number is set adequately high. I chose Chebychev polynomials and equally-spaced nodes to compute the approximate solutions for the Bellman equations. The solution was computed using the CompEcon 2012 Toolbox routine *dpsolve*.

In this context, Newton’s method uses an iterative process of linearizing the value function approximants using their derivatives with respect to the agent’s choice variables (l in this case) to identify the model solution; however, the formulation of the Bellman equation complicates this computational approach because the agent’s current reward is not a function of its current actions l . The lender chooses loan allocations to maximize its expected stream of dividend payments given the regulatory penalty. The lender’s current reward in (4), $f(K, L) = \nu K - g(K, L)$, is highly nonlinear in K and L but is unaffected by its current action, $f_l = 0$. As a result, computed solutions of the optimal lending policy are unstable, e.g., highly sensitive to the defined state space. To address this complication in deriving a numerical solution, I code a slightly different formulation of the Bellman equation, iterating the reward function forward one period

$$V(K) = \max_{l \geq 0} \{E[vK' - g' + \delta V(K')]\} \quad (9)$$

where $g'(K, l, \xi) = \gamma \max\{0, \kappa - \frac{(1-\nu)+\pi}{(1-\xi)l}\}^2(1-\xi)l$ is the upcoming regulatory penalty, which uses the state transition functions (1) and (3). This atypical formulation results in the same lending policy, the lender

Table 2: Empirical and simulated performance of the studied lender, annualized values (%)

	Empirical			Simulated		
	Mean	St. Dev.	[Min, Max]	Mean	St. Dev.	[Min, Max]
Return on equity	32.0	8.1	[10.0, 39.0]	31.9	6.4	[22.1, 41.7]
Net income/loans	5.3	1.3	[1.8, 6.5]	5.2	1.0	[3.6, 6.7]
Administrative costs/assets	11.9	1.6	[8.8, 14.2]	11.7	0.04	[11.7, 11.8]
Defaults/loans	3.0	0.2	[2.4, 3.3]	3.0	0.2	[2.6, 3.4]
Equity/loans	16.8	1.1	[14.1, 18.7]	16.7	0.2	[16.0, 16.6]

Note: Empirical values are derived from observations from an evaluation period of July 2009 to June 2012. Means and standard deviations are calculated by quarter, and the values are reported in annual terms. Simulated values are derived a Monte Carlo simulation with stochastic loan performance of the evaluation period with 100,000 draws. “Risky investments” comprises the credit and market portfolios of the FI.

chooses loan allocations to maximize its expected stream of dividend payments given the regulatory penalty, and a reward function with a nonzero first and second derivative in l , increasing the stability of the numerical solution.⁷

3. Results

This section describes the modeled optimal behavior of the lender and simulates the effects of a natural disaster on its operations. It also compares these simulation results to the experience of a geographically concentrated MSME lender during the 1998 El Niño.

3.1. Lender simulations

Lender simulations rely on the optimal lending policy generated using the calibration in Table 1. This policy identifies the amount of loans to originate given a level of equity, and the policy is examined across several conditions. First, I assess model performance under non-disaster conditions, the results of which are directly comparable to the empirical evaluation period of the modeled FI. Second, I simulate a disaster, assessing its effects, and the lender’s response. Third, I manipulate the magnitude of the regulatory penalty, simulate a disaster, and examine the effects of regulatory stringency on lender behavior.

3.1.1. Performance under non-disaster conditions

This section assesses model performance with respect to empirical performance during the evaluation period through Monte Carlo simulations. The model is calibrated for quarters so that El Niño, which occurs over a period of roughly three months, is captured in a single period. The empirical evaluation period is nine quarters in duration. For the Monte Carlo simulation, I run the model for nine periods 100,000 times, recording the means, standard deviations, minima, and maxima for several income and balance sheet indicators. To make the simulation 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 ϵ modeled in (8).

Table 2 provides the results. While several indicators are fairly consistent between empirical and model performance, perhaps the most relevant disparity is the difference in standard deviations for the ratio of equity to loans. This ratio is an approximation of and hereafter called the capital ratio. The larger empirical standard deviation for the capital ratio is most directly explained by lumpy dividend payments, which tended to occur annually. If I average each year’s dividends across quarters, the standard deviation reduces to 0.3%.

The primary result of interest in this pre-event analysis is that the simulated lender holds a capital buffer of 2.7 percentage points above the minimum requirement of 14%. This buffer is a response to the lender’s credit risk given capital market frictions and regulatory penalties in the model and is in the vicinity of the buffer held by the FI for which the model is calibrated.

⁷The Bellman equations (4) and (9) are not equivalent in several ways, e.g., the shadow prices of capital differs; however, my analyses are limited to the optimal lending policy.

3.1.2. Disaster simulation

Figure 1 illustrates model results for a disaster simulation. In the figure, the disaster occurs in Period 0. Eight quarters occur before the disaster and 20 following it. To isolate the effect of the disaster, I set the unexplained variation in nonrepayment from (8) equal to its mean, $\epsilon = 0$. The dotted gray lines capture this unexplained variation and represent 95% confidence intervals for each period based on $\text{var}(\epsilon)$. In other words, the solid blue line in the graphs identifies the expected performance of the simulated lender given the occurrence of the disaster, and the dotted gray lines indicate the degree to which other factors affecting nonrepayment are likely to influence performance in a single period. The y axes of these graphs tend to be standardized based on the initial value of the variable of interest. (E.g., for the first graph, all values for income are in reference to income in the initial period, $\pi_{-8} = 1.1 = 100\%$). Initial values are set at the mean of the steady state.

The disaster creates loan losses that lead to income losses. Income losses 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 originating fewer loans, disrupting the credit supply. The model predicts a contraction of about 16% of the portfolio.

While the lender responds to falling below minimum capital requirements, 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 supervisory stringency, that guide this behavior so that even if loan losses lead to a capital decline that remains above minimums, credit contraction occurs in the model.

3.1.3. Implications of regulatory stringency

This section explores the effect of the regulatory penalty on the optimal lending policy. The penalty calibration in the pre-event and disaster simulations (set at $\gamma = 100$) has two attractive features. First, the penalty the lender incurs due to the disaster is less than 40% of normal quarterly income, a level that seems reasonable as it is neither negligible nor does it eclipse income. Second, it illustrates the capital buffer created by this regulatory approach.

Figure 2 shows the effect of regulatory stringency on the optimal lending policy and capital ratio by examining a range of values for γ . The figure illustrates an important social tradeoff for central planners. 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.

3.2. Empirical evidence: Credit supply and the 1998 El Niño

The disaster simulation motivates examining whether the 1998 El Niño created the capital shortages and credit contraction the model predicts. 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.

In moving from the theoretical to the empirical analysis, it is worth considering how markets might respond to a slow-onset event such as El Niño. During the roughly three month period in which El Niño created torrential rainfall and flooding, credit allocations may understandably decline as borrowers and lenders wait for the rain to stop. If so, this decline would likely be apparent across all credit markets affected by the disaster. In contrast, the topic of interest is credit contraction following the event – does capital management seem to reduce the supply of MSME credit relative to other credit markets?

Figure 3 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 3, 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 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.

Table 3: Portfolio composition by lender type

	Commercial Banks		Municipal Cajas	
	Value (\$1,000)	% of Total	Value (\$1,000)	% of Total
Commercial	9,549,486	77	25,523	12
MSME	421,651	3	108,190	53
Consumption	1,334,091	11	72,016	35
Mortgage	1,089,131	9	-	-
Total	12,394,358		205,730	

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

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 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 3, 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 4 tracks Caja Trujillo's performance before, during, and following El Niño. The graphs in this figure are overlaid 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. As noted in Section 1.1.2, community lenders such as Caja Trujillo use their informational monopoly to capture rents (Agarwal and Hauswald, 2010) and so the caja has grown rapidly in the past two decades (from \$9 million in outstanding loans in January 1997 to \$420 million in December 2013). Thus, while the modeled lender converges toward its steady state distribution after a disaster, the caja does not have a steady state defined in absolute values.

Before discussing El Niño, consideration of the context is helpful. 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 El Niño 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 some agricultural commodities such as mangoes. The most devastating consequences of the El Niño 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 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, and 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.

Consistent with the framework, 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. 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. Figure 5 compares the percent change in loan allocations from commercial banks to those of Caja Trujillo. 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.

The example of Caja Trujillo provides some anecdotal evidence of the principles underlying the theoretical model. As noted in Section 3.1.3 and illustrated by Caja Trujillo, credit contraction does not require falling below minimum regulatory requirements, but can be driven by internal capital targets. Caja Trujillo’s internal targets seemed to change, growing as El Niño related loss provisions grew and falling after provisions stabilized.

The empirical example also illustrates the ability of lenders to dynamically manage their realization of losses through loan restructuring, a condition not included in the model. Consistent with other jurisdictions, regulations in Peru allow lenders to hold fewer provisions for problem loans that have been restructured (Superintendencia de Banca, Seguros, y AFP, SBS, 2008, is the current law). These rules motivate proactive management; however, they can also be used strategically when lenders experience declines in portfolio quality. Smoothing the realization of losses in this way can protect lender solvency and reduce credit contraction, but also contributes to uncertainty in financial markets regarding the true extent of losses from a severe event.

4. Model extension: Disaster-contingent claims

The challenges disaster create for lending to MSMEs are sobering, especially given the importance of credit access for minimizing disaster losses and facilitating recovery (Noy, 2009). The seminal work Diamond (1984) on lending under opacity offers a potential solution 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 theoretical model to evaluate this contingent contract and its potential effect on lender behavior.

Indemnity insurance, which makes payments on policyholder losses, is vulnerable to the same asymmetric information problems as credit markets and so would seem quite difficult to implement in this context. 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.⁸ Thus, rather than insuring returns on an opaque portfolio, parametric contracts directly insure the observable risk of a severe disaster, limiting moral hazard and adverse selection (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. Khalil et al. (2007) find a strong relationship between the index and rainfall in the region; however, severe El Niño has not occurred since the development of the insurance so it has not yet been tested in practice.

The El Niño insurance uses the same Niño 1+2 index of ocean temperatures discussed in Section 2 as the sole basis of payments. The contracts offered in Peru typically have a linearly increasing payout structure. For example, one contract has a trigger of 24.5° and exhaustion point at 27°, 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

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

⁸While 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).

where t is the measure of ocean temperature. Discussions with insurers and reinsurers suggest that for this risk the loads for commissions, administration costs, etc., would be approximately 75% of the actuarially fair rate, resulting in an annual premium rate of 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.⁹

4.1. Model with insurance

As an update to the dynamic model, the lender can buy a sum insured $q \geq 0$ at premium rate p and receive a payout based on the function $i(t)$. The lender's new income equation is

$$\pi = r(1 - \xi)l - r^d d - h(l) - \xi l - pq + qi(t).$$

Figure 6 illustrates results for the model in which the lender transfers its risk. The dotted blue line replicates the disaster simulation from Section 3.1.2, 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.

The lender chooses to insure. At the actuarially fair rate, the lender fully insures the credit and revenue exposure (99%). At the loaded rate and current calibration, the lender insures 35% 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 70% 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 during the period following the disaster. Because the insurance addresses the disaster-related credit risk, the lender operates with a smaller buffer above minimum requirements, increasing the credit supply under non-disaster conditions. Under the actuarially fair case, loan allocations increase by 12% under non-disaster conditions (5% in the loaded case).

Given the model limitations discussed in Section 3.2 (e.g., that it does not capture opportunities for loss smoothing such as strategic loss provisioning), its estimate of optimal insurance should be considered an upper bound. Another limitation of the current calibration of the theoretical model is that it evaluates disaster risk only in the context of loan performance during the evaluation period. If the modeled lender is vulnerable to other systemic shocks (e.g., from currency, commodity price, or interest rate fluctuations) but those risks did not occur during the evaluation period the calibration ignores them. A modeled lender vulnerable to several systemic risks would set capital reserves based on the multivariate distribution of extreme events. Risk transfer in this context is still predicted to address credit contraction for the insured event; however, multifactor vulnerability dampens the degree to which risk transfer reduces capital buffers. The variety of risks often facing FIs motivate comprehensive risk management strategies that include layering financial mechanisms, flexible capital buffers for small to moderate risks and contingent claims for severe risks.

4.2. 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 an external insurance market, bank holding companies might integrate disaster-contingent claims in their internal capital markets. I speculate that they already do albeit informally. While not studying natural disasters, De Haas and Van Lelyveld (2010) find that, in the midst of a local banking crisis, local 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 6; without such internal pricing, disaster-contingent claims create perverse incentives for subsidiaries.

Internal contingent-claims markets apply not only to MSME lending within a bank holding company, but any banking subsidiary of a parent. 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, such as the FI for which the model is calibrated and ProCredit, internal capital markets based on an observable trigger, such as the Niño 1+2 index, would better align the incentives of the parent and subsidiary (Diamond, 1984; Stein, 2002).

⁹For readers interested in learning more about the El Niño insurance, which has several interesting features, please see [The Economist \(2014\)](#); [GlobalAgRisk \(2013\)](#).

5. Discussion

This paper discusses supply driven contraction in MSME credit markets due to natural disasters. It proposes a framework to understand this problem: 1) MSMEs are often opaque and highly vulnerable to disasters; 2) overcoming information problems frequently motivates lenders to specialize geographically, creating portfolio concentrations of disaster risk; 3) lending to opaque borrowers increases capital market frictions for lenders, challenging disaster recovery; and 4) opacity constrains supervision, increasing emphasis on minimum capital requirements, which exacerbate capital market frictions. The framework is formalized in a dynamic theoretical model to test lender behavior under these conditions, finding that capital market frictions and regulation cause the lender to maintain a capital buffer above minimum requirements to manage its risk. Following a disaster, systemic loan losses motivate the lender to contract credit. Supply-driven credit contraction is concerning as the period following a disaster is one in which demand for credit increases (Berg and Schrader, 2012; Noy, 2009).

Model results are compared to the performance of an MSME lender during the 1998 El Niño, which caused catastrophic flooding in Peru. The lender contracted credit in preparation for and following El Niño due to capital management, reducing lending by about 12% from pre-event levels at its lowest. In contrast, commercial banks, which specialized in lending to corporations, redirected capital to affected regions, expanding credit. These results are consistent with the framework, which suggests that existing credit market disparities between MSMEs and large firms are likely to increase following a disaster, and support evidence from other credit market shocks (e.g., Khwaja and Mian, 2008).

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, while information infrastructure such as credit bureaus seem most fundamental, 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 a contingent claims contract in Peru, El Niño insurance, which makes payments, not on policyholder losses, but using an objective measure of the disaster. This recently developed mechanism seems almost perfectly suited to manage the disaster risk problem of MSME lenders in northern Peru as it transfers an observable systemic risk from their opaque portfolios. The theoretical model shows that it increases lender leverage and dramatically 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, Yvonne Aguirre Polo in particular. I would like to thank Mario Miranda and Jerry Skees for their mentoring, conceptual contributions, and early reviews of this paper, and Grant Cavanaugh for his contributions to estimating the probability of El Niño. This manuscript also benefited from the reviews and insightful comments of Paul Shea and Ruben Lobel. 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 financial 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 German development agency.

Appendix: Fitting the Niño 1+2 distribution

NOAA measures Niño 1+2 using a combination of data from ocean buoys, satellite sensors, and transoceanic liners. Data are available from 1950¹⁰; however, the amount of buoys increased significantly in the 1970s.

¹⁰<http://www.cpc.ncep.noaa.gov/data/indices/ersst3b.nino.mth.81-10.ascii>

One of the earliest reanalysis datasets, NOAA’s Climate Prediction Center Merged Analysis of Precipitation (CMAP), 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 7 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 on El Niño (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 2, 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 t exceeding 24.5° on the Niño 1+2 Index as a severe El Niño event.

The probability of severe El Niño is assessed using maximum likelihood estimation (MLE) of the generalized extreme value (GEV) distribution. This distribution is commonly used for estimating 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 8 provides a histogram of the index values and the estimated probability density function. Based on this analysis, the annual probability of severe El Niño is

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

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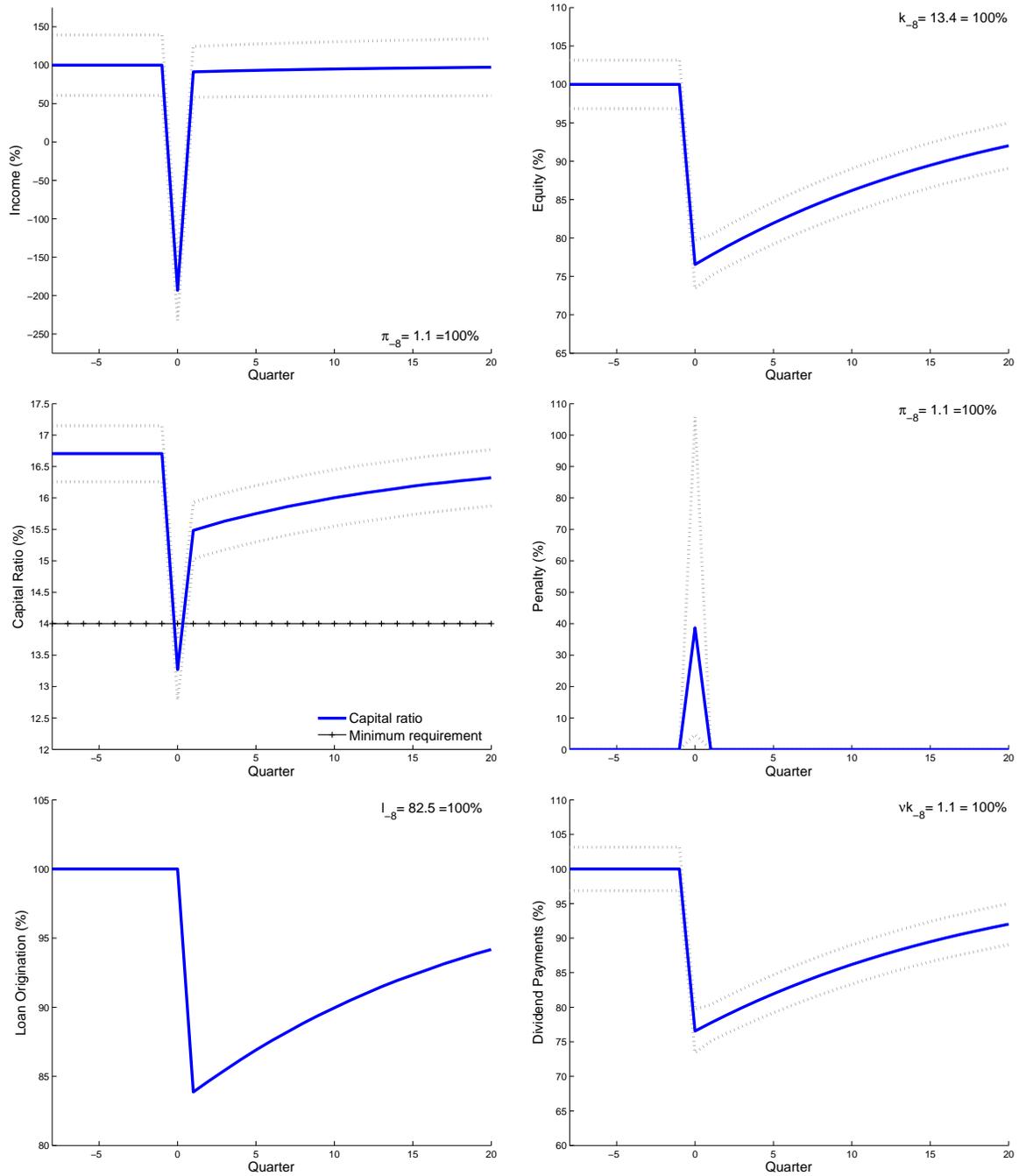
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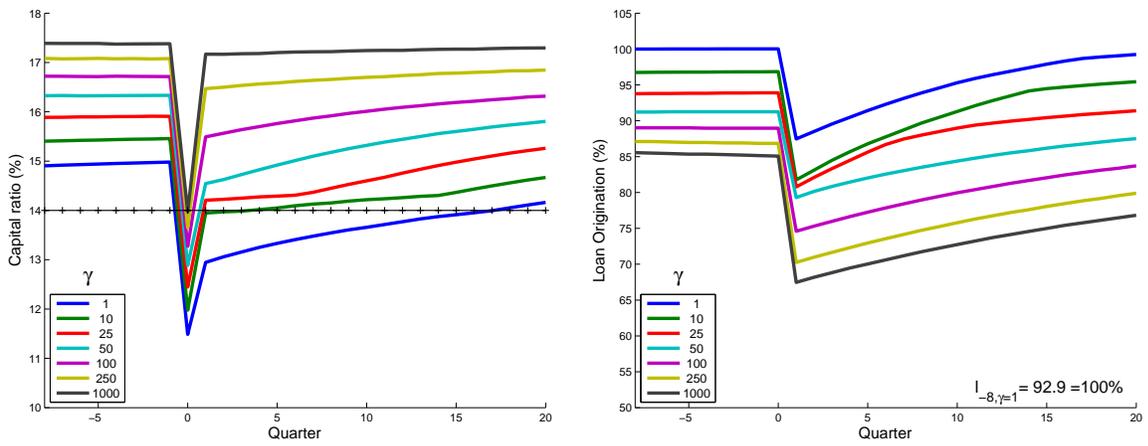
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Figure 1: Simulation results



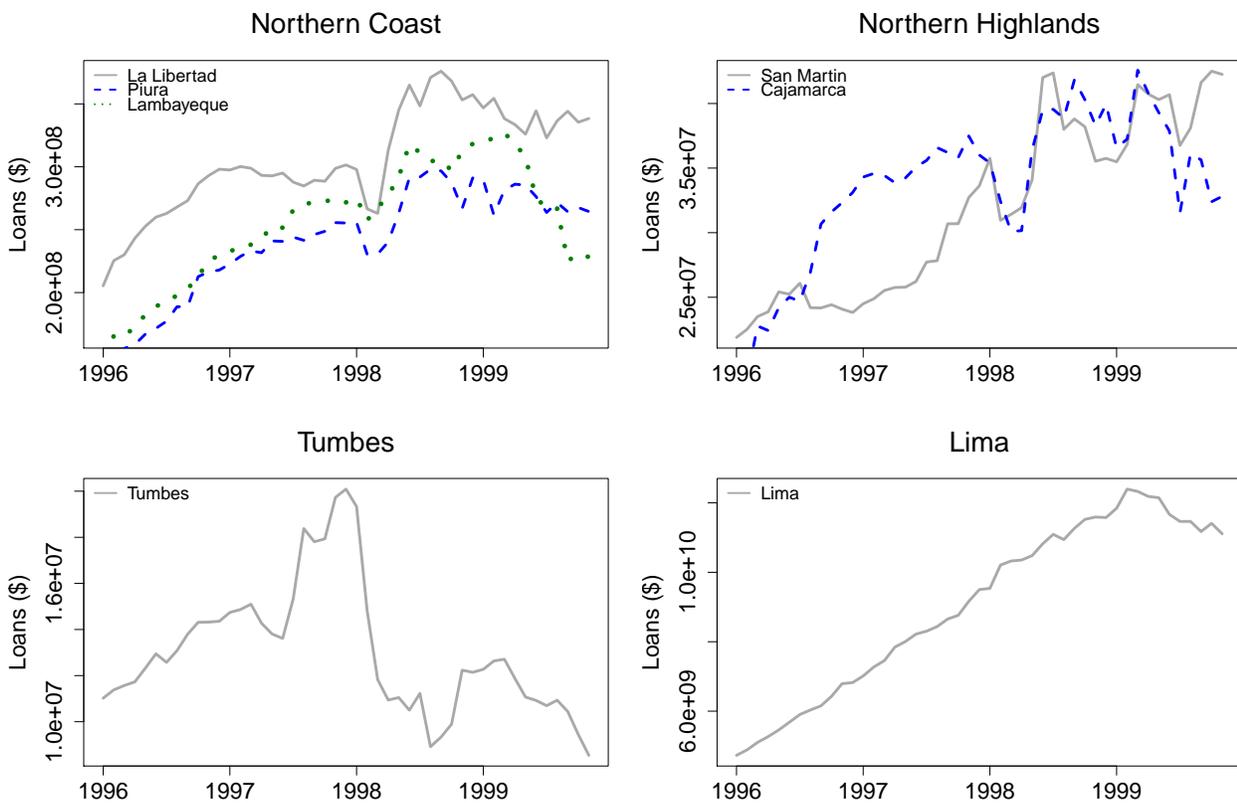
Note: Simulation results demonstrate the behavioral, financial, and operational consequences of El Niño risk for the modeled lender. The disaster creates equity losses that motivate the lender to contract credit. Except for the capital ratio, they y axes on all figures are configured as a percent of the mean value of the non-disaster steady state for the variable of interest. The y axis for the regulatory penalty is configured as a percent of quarterly income.

Figure 2: Supervisory stringency, capital targets, and lending



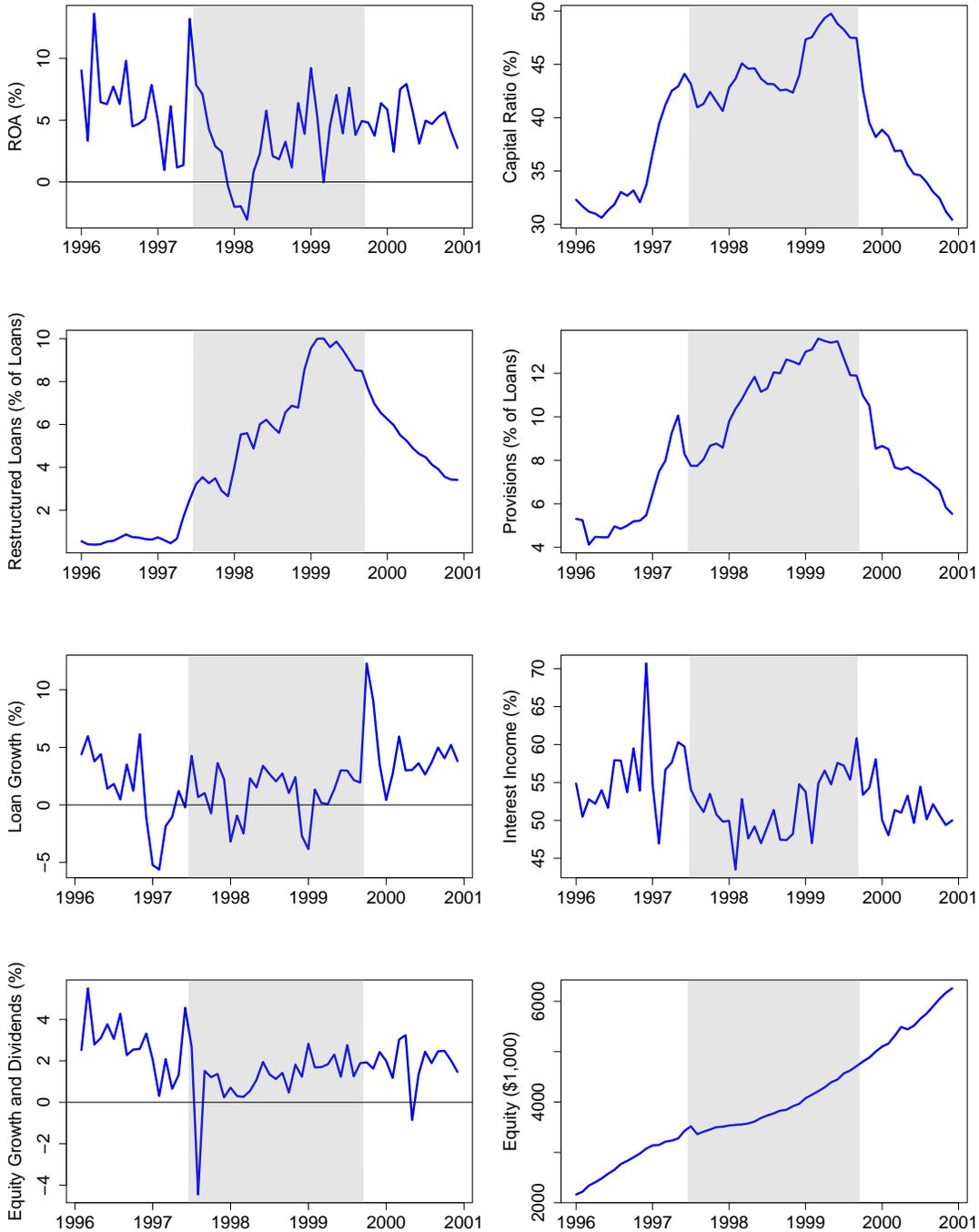
Note: More stringent capital requirements (higher levels of γ) motivate lenders to hold higher capital ratios and lend less. Following a disaster, this stringency increases credit contraction.

Figure 3: Regional Credit from Commercial Banks and the 1998 El Niño



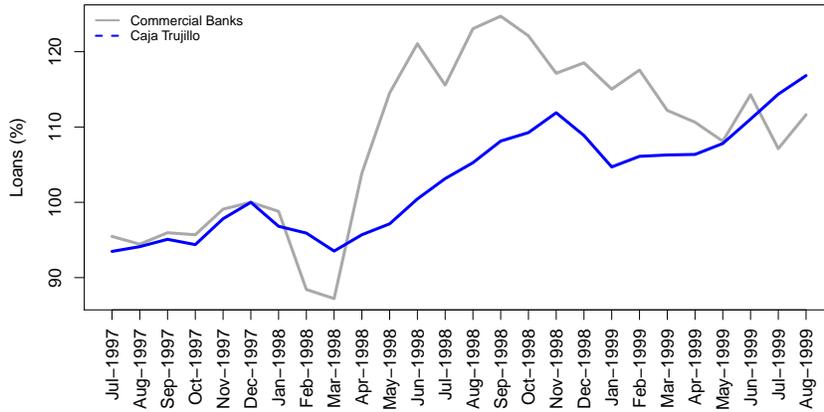
Note: The 1998 El Niño created severe rain and flooding in northern Peru, reducing loan allocations but also leading to increased investments following the event among commercial banks. Credit allocations in Lima, which is in central Peru, were not affected.

Figure 4: Financial Performance of Caja Trujillo during the 1998 El Niño



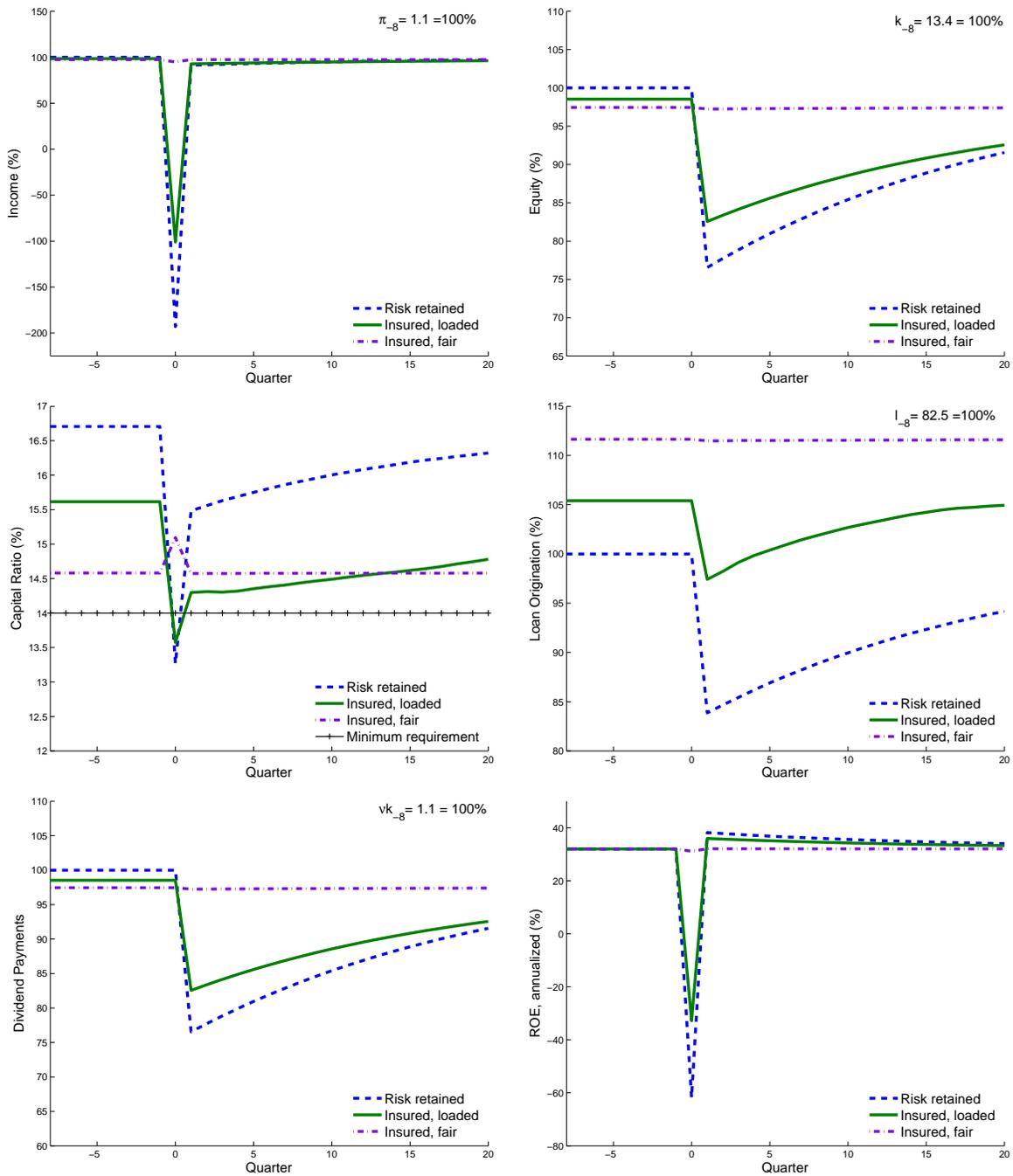
Note: El Niño damaged portfolio quality, reducing income and equity and leading to some credit contraction; however, the caja's substantial capital reserves and the significant income opportunities in local credit markets facilitated recovery. ROA is in annualized values. Interest income is a percent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

Figure 5: Loans from commercial banks and Caja Trujillo in La Libertad



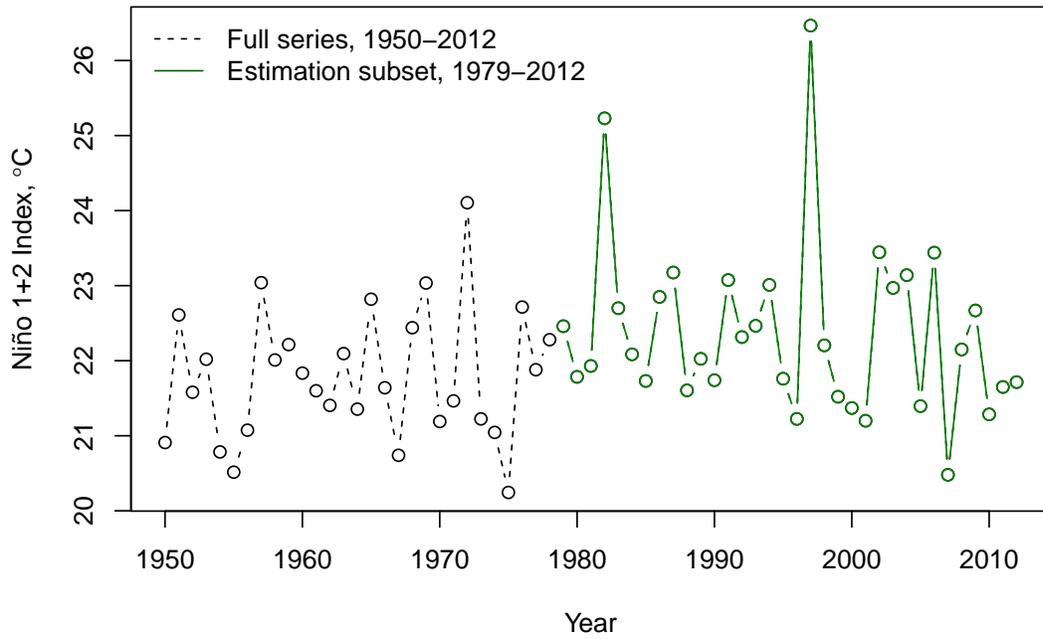
Note: Following El Niño, commercial banks expanded credit by approximately 25% in La Libertad to meet the needs of its customers, mostly large firms. In contrast, capital management related to loan losses challenged the ability of Caja Trujillo to meet the demands of its MSME customers. The y axis is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

Figure 6: Simulation, insured



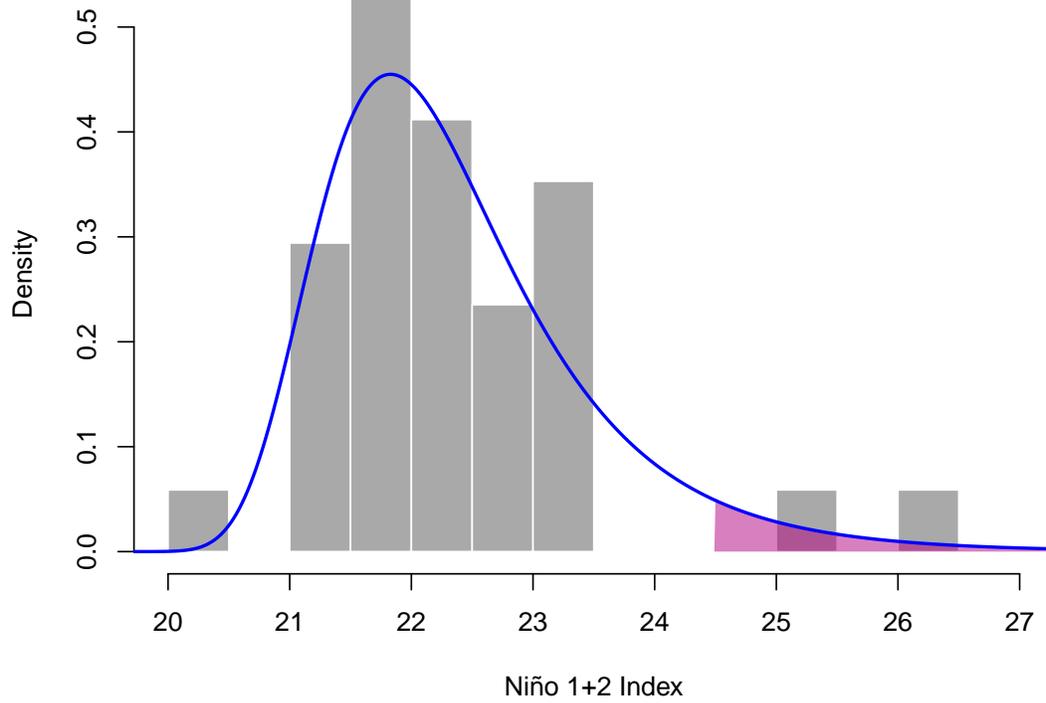
Note: Insurance reduces the financial and operational disruptions of severe El Niño. As a result, the lender operates with a smaller buffer above minimum requirements, increasing the credit supply under non-disaster conditions.

Figure 7: 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.

Figure 8: Histogram and GEV distribution



Note: The histogram and MLE estimation of the generalized extreme value distribution for the Niño 1+2 Index are shown. The shaded area under the curve identifies the probability of a severe El Niño, which is 4.6% annually.