Strengthening Local Credit Markets Through Lender-Level Index Insurance

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Abstract

This paper considers lender-level index insurance as a means of expanding access to credit in disaster-prone communities. In this approach, the lender transfers the disaster risk of loans in its portfolio by contracting on an observable measure of the catastrophe. I develop and calibrate a dynamic, stochastic model using data from a community lender in Peru that is vulnerable to El Niño-related flooding. The modeled lender can insure against El Niño using an index-based product that is available for purchase by financial intermediaries in Peru. I examine how premium rates, basis risk, and background risk may influence the lender’s insurance decision and credit supply. Overall, the results suggest that lender-level index insurance holds promise for reducing disaster-related credit supply shocks and expanding credit access in vulnerable communities.

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1 Introduction

Natural disaster exposures are ubiquitously under-insured. For example, about 70 percent of nat-ural disaster losses in the last decade were uninsured (2008-2017, Swiss Re, 2018). This insurance gap affects not only disaster-exposed firms and households, but third parties connected to them. Recent research examines the uninsured disaster exposures of local credit markets, noting that dis-asters can cause spatially concentrated loan defaults. Laux et al. (2017) consider the low take-up of earthquake insurance and the exposure of California mortgage lenders. Collier and Babich (2017) examine lending in community credit markets of developing and emerging economies. They find that disaster-related losses on existing loans erode lenders’ equity capital, causing them to reduce the credit supply after the disaster. In turn, these credit market frictions seem to exacerbate the economic consequences of the disaster by delaying the recovery of affected firms and households (Del Ninno et al., 2003; Noy, 2009). These findings highlight the importance of reducing the cata-strophe insurance gap. However, in developed and developing countries alike, getting households and businesses to insure remains a formidable challenge and so creates a need for lenders and other third parties to manage their disaster risks.

This paper considers an approach in which lenders transfer their portfolio-concentrations of disaster risk – the lender, rather than the borrowing household or business, insures its risk. The paper’s primary research question is how lender-level risk transfer may influence access to credit for disaster-prone communities in developing and emerging economies. I consider both ex ante and ex post access to credit. Regarding ex post access, I assess how transferring disaster risk is likely to affect credit supply shocks created by the disaster. Regarding ex ante access, I assess whether transferring disaster risk may influence the self-insuring strategies of the lender during non-disaster conditions, for example, whether it more fully leverages its capital, lending more per dollar of equity.

The focus and modeled application is on financial intermediaries (FIs) lending to households and small and medium enterprises (SMEs) in developing and emerging economies. I refer to these FIs as “SME lenders” though “community lenders” would also be appropriate.

I develop a dynamic, partial equilibrium model to examine the behavior of a representative lender under risk. The credit portfolio of the FI is exposed to a systemic catastrophe and uninsurable background risks. The FI manages a stock of equity and maximizes its expected, discounted stream of returns through its lending decisions. The lender must meet minimum capital requirements, incurring compliance costs if its capital falls too low. I calibrate the model for an SME lender
in Peru that is vulnerable to severe El Niño-related flooding. The calibration data are from the lender, which conducted a risk assessment survey among its field office and credit risk managers, and its banking regulator, which provided monthly income and balance sheet data.

The model’s mechanics are consistent with previous research (e.g., Collier and Babich, 2017; Van den Heuvel, 2009): in response to losses on existing loans from a catastrophe, the lender contracts credit, reducing loan allocations to bring them in line with a smaller equity capital base. The risk of these shocks motivates the lender *ex ante* to maintain a capital buffer above minimum requirements, which has the effect of reducing the credit supply in non-disaster conditions.

Next, I consider the development of a market to transfer the lenders’ catastrophe risk through index insurance.\(^1\) Index insurance makes payments using an objective measure of an adverse event (e.g., deficit rainfall at local weather stations as a measure of drought). I model the lender’s risk transfer decision using an El Niño index insurance product that is available for purchase by FIs in Peru. I examine the model under several scenarios. First, I assess the lender’s behavior when insurance is priced at the actuarially fair rate and at a loaded rate. The loaded rate is the price that a lender might pay in the private market, and I use the rate for El Niño insurance as a benchmark. Second, I assess the effect of background risk, the presence of other uninsured exposures, on the lender’s catastrophe insurance demand. This assessment examines how demand may change across settings in which disaster risk is a first-order concern versus those in which other risks (e.g., economic recessions, commodity price risks) pose a greater threat. Finally, I assess the effect of basis risk, the potential mismatch between the index insurance payment and the losses incurred by the lender, on the lender’s insurance demand.\(^2\)

I find that insurance has the potential to both reduce *ex post* credit contraction and expand the *ex ante* credit supply in this context. The uninsured FI reduces lending by 15 percent following the modeled natural disaster. An FI purchasing actuarially fair insurance would fully transfer its risk so that its lending is unaffected by the disaster, and an FI purchasing insurance at the loaded rate would partially transfer its disaster risk and reduce lending by about 9 percent following a severe event.\(^3\) Insurance also speeds the lender’s recovery such that the credit supply returns to pre-event levels more quickly. Regarding *ex ante* credit access, insurance motivates the FI to operate with a smaller capital buffer as it reduces uncertainty in its returns, and so increases lending.

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1. While I refer to financial risk transfer as “insurance,” Cummins and Weiss (2009) describe a variety of structures that could be used in this setting such as derivatives (e.g., see their Figure 10 and accompanying text).
2. As a common example of basis risk, suppose that an index insurance product insures against low rainfall using weather station measurements. Basis risk describes the possibility that rainfall at the policyholder’s location may differ from that at the closest weather station.
3. The results illustrate the corporate risk management theory of Froot et al. (1993): financing frictions in bad states of the world can motivate risk neutral decision-makers to insure, even at actuarially unfair rates.
estimate that actuarially fair insurance would expand access to credit by about 8 percent and loaded insurance by about 5 percent during non-disaster conditions.

I also find that greater background risk and basis risk reduce \textit{ex ante} credit expansion as index insurance less effectively transfers lenders’ earnings risks. While basis risk reduces the optimal insurance coverage, insuring the disaster risk has some benefit even when basis risk is large. Background risk appears more problematic than basis risk. When background risk is large relative to disaster risk, the modeled lender does not insure. Instead, background risk motivates the lender to target a higher capital ratio, and this additional capital self-insures the lender’s disaster exposure. Thus, large background risk reduces the benefits of transferring the lenders’ disaster risk and so may preclude the development of effective lender-level disaster insurance markets in some settings.

This paper contributes to several lines of research. First, it adds to a literature on insurance market development. Insurers and development organizations have engaged in substantial experimentation to reduce the insurance gap through microinsurance and weather index insurance (e.g., Barnett and Mahul, 2007; Carriquiry and Osgood, 2012; Chantarat et al., 2013; Mahul et al., 2012). For example, several pilot projects have pursued a compelling model that bundles index-based microinsurance with credit for smallholder farmers including in Malawi (Giné and Yang, 2009), Peru (Carter et al., 2007), Kenya (Greatrex et al., 2015), and Ethiopia and Senegal (Norton et al., 2014; Spiegel and Satterthwaite, 2013). These pilots have shown promise and provided important insights. However, overall progress on expanding insurance coverage has been slow. Households and SMEs in developing markets do not buy insurance products that economists initially predicted they would (Binswanger-Mkhize, 2012). For example, Giné and Yang (2009) find that smallholders tend to prefer credit alone over the bundled credit and microinsurance product offered in Malawi. Why take-up of microinsurance is low remains a puzzle, though studies tend to highlight liquidity constraints, basis risk, and counterparty risk (i.e., trust of the insurer, Cole et al., 2013; Karlan et al., 2014). To my knowledge, the idea of transferring a lender’s disaster risk at the portfolio level originates in the academic literature with Skees et al. (2007) who describe their field work in Peru and Vietnam. Several recent pilot projects are planning portfolio-level products for lenders including in Indonesia, Jamaica, and the Philippines (World Bank, 2018). This paper contributes by analyzing a complementary approach to microinsurance for reducing the catastrophe insurance gap. While this approach does not address the direct losses of households and SMEs, it would seem to represent meaningful progress toward reducing the consequences of catastrophes.

Moreover, background risk and basis risk are important considerations in this context and are part of larger risk management and insurance literatures. The presence of uninsurable background
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Risk can affect demand for insurance or prevention (e.g., Doherty and Schlesinger, 1983, and recently Courbage et al., 2017; Hofmann et al., 2018). A main theme of that research is that insurance premiums reduce the wealth of policyholders and so increase their susceptibility to other shocks. Background risk may be large in developing and emerging markets due to low insurance penetration, political instability, etc. Basis risk has been a topic of interest for index-based risk transfer products in both developed (Cummins et al., 2004; Doherty and Richter, 2002; Golden et al., 2007) and developing (Chantarat et al., 2013; Clarke, 2016) markets. For example, Cummins et al. (2004) examine hedging insurers’ hurricane losses in Florida using index-linked securities. They find that large insurers (above the median) can hedge hurricane losses almost as effectively using a state-level loss index contract as they can using an indemnity-based contract. They find that basis risk is larger for smaller insurers, though some may still hedge effectively using index-based contracts. Also, Clarke (2016) models the effects of basis risk on index insurance demand. He builds on the work of Doherty and Schlesinger (1990) who consider how contract nonperformance (a type of background risk) affects demand for insurance. Clarke’s insight is that basis risk is an example of this nonperformance. Modeling risk averse households, he shows that basis risk leads to a non-monotonic relationship between index insurance demand and risk aversion, initial wealth, and insurance premiums. By examining background risk and basis risk, I intend to build on insights from these literatures for a more complete analysis of the lender-level products considered here.

Second, the paper adds to a literature on the disaster risks of credit markets (e.g., Laux et al., 2017). Disasters have been shown to increase demand for credit but also credit constraints following Hurricane Sandy in the New York area (Collier et al., 2017), volcanic eruptions in Ecuador (Berg and Schrader, 2012), and flooding in Bangladesh (Del Ninno et al., 2003). Disasters can also create systemic losses for 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). Siamwalla et al. (1990) finds formal and informal rural lenders were ailing and unable to meet credit demand for consumption loans following droughts in Thailand. Using a panel of SME lenders, Collier and Babich (2017) conclude that credit contraction following natural disasters is due to lenders’ capital constraints – their difficulty replacing equity lost during the disaster. My

Schlesinger (2013) defines background risk as “the presence of other risks” besides the considered insurable risk. A large decision-making literature builds on Gollier and Pratt (1996) who examine the specific effects of background risk on risk-averse expected utility maximizers. They introduce a condition on the utility function, called “risk vulnerability,” to overcome certain counter-intuitive consequences of background risk in their setting. Eeckhoudt and Gollier (2013) provide a review of that decision-making literature. While findings from that literature inform this research, I do not model a risk-averse expected utility maximizer. Instead, I use the term “background risk” in the broader sense described by Schlesinger (2013).

Collier and Babich (2017) observe that community lenders in developing and emerging economies lend less after
research contributes by considering how insuring the lender’s risk may reduce disaster-related credit constraints.\footnote{This paper is closest to Collier and Skees (2012) and complements and extends their research. They profile a spreadsheet-based, banking simulation tool, which they used for educational purposes with lenders in Peru. In their model, the user provides lending and insurance decisions and examines the effects of a severe El Niño. In contrast, I develop a dynamic, theoretical model, calibrate it for a representative SME lender in Peru, and jointly identify its optimal lending and insurance decisions. This approach provides a richer setting to examine the lender’s response to the disaster and how the ability to insure influences the optimal lending decision. I also add analyses of background risk and basis risk. My model also complements the theoretical contributions of Collier and Babich (2017). Their model is broader and allows for richer disaster variation (e.g., the possibility of multi-period disasters) while mine is more narrowly framed to the insurance problem considered here.}

Third, it adds to a finance literature on lending under asymmetric information dating back to Diamond (1984). SME lending often uses relationship-based strategies that allow loan officers to screen and monitor borrowers due to limited objective data on small firms (e.g., credit scores, Berger et al., 2005). In turn, these relationship-based decisions are difficult to value externally and so result in informationally opaque portfolios of SME loans and so can create capital market frictions (Stein, 2002). Diamond proposes that if the returns of opaque borrowers are correlated with an observable risk (e.g., interest rate risk), a contingent contract should be used to transfer the observable risk. My setting fits Diamond’s description. The index structure reduces informational asymmetries between the insured and insurer relative to indemnity-based insurance (Doherty and Richter, 2002; Finken and Laux, 2009), and so would seem to be well suited for transferring the risks of SME lenders.

Finally, this research contributes to a public economics literature on disaster policy. Natural disasters tend to reduce economic growth (Klomp and Valckx, 2014; Cavallo and Noy, 2011), but more developed credit markets mitigate disaster-related economic disruptions (Noy, 2009). Moreover, disaster risk limits credit market development, especially in rural communities (e.g., Barnett et al., 2008). Expanding access to credit remains an important public policy objective in many developing and emerging economies: half of SMEs in developing countries identify access to financing as an operational constraint (Stein et al., 2013). My research indicates that lender-level index insurance can, at least in some settings, reduce credit market disruption and expand the credit supply in disaster-prone regions. These findings may help motivate public policies that facilitate the transfer of lender’s disaster exposures, which I discuss in Section 5.3.

The paper proceeds as follows. Section 2 describes the theoretical model. Section 3 describes the setting and model calibration. Section 4 describes the results. Section 5 considers the effects of disasters. They consider two possibilities. First, the disaster may undermine profitable lending opportunities by reducing demand for credit or destroying the collateral of potential borrowers. Second, the disaster may create losses on existing loans and so reduce the lender’s equity. They find support for the latter explanation as lenders with low capital ratios before the disaster are the ones who lend less afterward.
of background risk, basis risk, and regulatory supervision. Section 6 concludes.

2 Theoretical Model

I develop a dynamic, partial equilibrium of a representative SME lender which is exposed to systemic disaster risk. The model setting leverages several stylized facts from previous research. I list them and provide example references here. The lender

- specializes geographically and so is exposed to spatially correlated risks (Agarwal and Hauswald, 2010; BCBS, 2010).
- incurs convex operational costs (Agarwal and Hauswald, 2010).
- is capital constrained; it is unable to attract additional equity investments (Campello, 2002; De Haas and Van Lelyveld, 2010).
- is regulated based on its capital ratio and faces convex costs if capital falls below regulated minimums (Calem and Rob, 1999).
- is a price-taker regarding interest rates, and rates do not depend on the disaster (Collier and Babich, 2017).

A dynamic model has several advantages here over a static or two-period version. Most importantly, it accommodates examining the duration of recovery. As the results show in Sections 4 and 5, the dynamics are an important aspect of the problem.

In Online Appendix A.1, I relax several of these assumptions to examine their effects. In particular, I relax the capital constraints assumption and show that the model then reduces to a static problem. I also relax the assumption that the lender cannot fully diversify its disaster risk and show that it is undiversifiable risk that reduces the credit supply.

Collier and Babich (2017) conclude that capital constraints are the primary cause of disaster-related credit contraction in their study of SME lenders and that affected lenders rebuild their capital through retained earnings. The type of SME lender that they study and that is modeled here is often privately held or even owned by the local municipality. Their findings suggest highly capital constrained lenders and so motivate their approach of assuming that the lender cannot raise additional equity. I follow their approach to modeling capital constraints as it seems to capture the core economic tradeoffs regarding whether to insure in this setting.

While other approaches to modeling capital constraints could complicate the core exposition here, they might be useful in future research. For example, Froot et al. (1993) consider convex capital costs such that raising capital is more costly during adverse states of the world. Their approach would require adding a decision variable regarding raising additional capital. Extending the model in this way could be useful in settings where equity capital markets are more developed than what we observe here.
2.1 Lending Decisions

A representative lender maximizes its expected, discounted stream of returns over an infinite horizon. The lender manages a stock of equity capital $K_t$ and is unable to attract additional equity investments. The lender can originate one-period loans $l_t$ at an interest rate $r$ or invest in other FIs and receive a risk free return $r_f$. Lending is exposed to the production risks of borrowers leading to random nonrepayment rate $\xi_{t+1} \in [0,1]$. A portion of the production risk is associated with natural disaster exposure. The lender can choose to lend more than its equity $K_t$ by borrowing at the risk free rate.

The lender also incurs operational costs $h(K_t, l_t)$. Some are a function of its equity ($K_t$), overhead costs such as back-office labor and real estate costs, taxes, bank licensing and regulatory fees. Other costs are a function of its lending decisions ($l_t$) such as origination and monitoring costs. These costs are separable, increasing, and convex ($\partial h_t/\partial K_t, \partial^2 h_t/\partial K^2_t, \partial h_t/\partial l_t, \partial^2 h_t/\partial l^2_t > 0$). Thus, its income function is

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

where $d_t \equiv l_t - K_t$. If $d_t < 0$, the lender is a net creditor to other FIs; if $d_t > 0$, it is a net debtor.

The lender is monitored by its capital ratio,

$$c_{t+1} = \frac{K_t + \pi_{t+1}}{(1 - \xi_{t+1})l_t}.$$ 

Thus, the capital ratio is evaluated after the lender has realized any returns from the period such that its capital is represented by initial equity and current income (or losses) and, in the denominator, the value of its loan portfolio is adjusted to account for non-repayment. If the capital ratio falls below the minimum requirement $\kappa$, the regulating supervisor responds with increasingly invasive penalties. This penalty is

$$g_{t+1} = \begin{cases} 
\nu(\kappa - c_{t+1})^2(1 - \xi_{t+1})l_t & \text{if } c_{t+1} < \kappa \\
0 & \text{o.w.}
\end{cases}$$

The penalty is increasing in the amount that the capital ratio falls below minimum requirements

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8I model operational costs as $h(K_t, l_t) = \alpha l_t + \beta l_t^2 + \gamma K_t + \zeta K_t^2$ in the numerical analyses in Section 3. While assuming that costs are convex in loans is sufficient to solve the dynamic problem, assuming that costs are convex in both loans and equity improves the stability of the numerical analysis. Model results are qualitatively consistent under both sets of assumptions; however, the latter assumption facilitates model extensions and robustness tests in Section 5.
and is scaled based on the size of the lender, as measured by outstanding loans. The lender retains any earnings so that its equity the following period is defined by

\[ K_{t+1} = K_t + \pi_{t+1} - g_{t+1}. \]

In sum, the lender solves the problem

\[
\max_{l_t \geq 0} \sum_{t=1}^{\infty} \delta^t E[\pi_{t+1} - g_{t+1}]
\]

\[ \text{s.t., } \pi_{t+1} = rl_t - rf(l_t - K_t) - h_t(K_t, l_t) - \xi_{t+1}(1 + r)l_t \]

\[ c_{t+1} = (K_t + \pi_{t+1})/((1 - \xi_{t+1})l_t) \]

\[ g_{t+1} = \nu \max \{0, \kappa - c_{t+1}\}^2 (1 - \xi_{t+1})l_t \]

\[ K_{t+1} = K_t + \pi_{t+1} - g_{t+1} \]

where \( \delta \) is the discount rate. The first order condition for this model is

\[
V_t : \ E[(1 + \delta \lambda_t) (\pi_t - g_t)] \leq 0 \tag{2}
\]

\[
= E[(1 + \delta \lambda_t) (r - rf - h_t - \xi_{t+1}(1 + r) - g_t)] \leq 0 \tag{3}
\]

where \( V_t \) is the lender’s value function, \( \lambda_t \) is the shadow price of equity capital, and I use the compact notation \( V_t \equiv \partial V_t / \partial l_t. \) The term in the second parentheses, \( (\pi_t - g_t) \), shows that the optimal lending policy balances expected marginal profits and penalties. The dynamic nature of the problem adds the term in the first parentheses, \( (1 + \delta \lambda_t) \), which considers the possibility that loan losses will constrain its ability to lend in future periods, captured in the shadow price of equity capital (\( \lambda_t \)). See Online Appendix A.1 for additional analysis and Silberberg (1990) or Seierstad

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9 The model describes a regulated lender, which is consistent with the Peruvian FI for which the model is calibrated in Section 3. Generalizing the model to unregulated lenders is straightforward as potential investors and credit rating agencies evaluate lenders by their capital ratios. In the panel of SME lenders from developing and emerging economies studied by Collier and Babich (2017), 60% of lenders are regulated and that both regulated and unregulated lenders with lower capital ratios lend less after disasters.

10 The inequality in the first order condition emerges from the constraint that lending is non-negative. Let \( V_t = \mu_t \). The non-negativity constraint results in a complementarity condition such that \( l_t \geq 0, \mu_t \leq 0 \) and \( l_t > 0 \implies \mu = 0 \).

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

\[
V_t : \ E[\pi_{t+1,l} - g_{t+1,l} + \delta \lambda_t K_{t+1,l}] \leq 0
\]

\[ = E[\pi_{t+1,l} - g_{t+1,l} + \delta \lambda_t (\pi_{t+1,l} - g_{t+1,l})] \leq 0 \]

where \( \lambda_t \equiv V_{K_{t+1}} \). Because \( \lambda_t \) is the partial derivative of a function, it cannot be passed through the expectation. This nonlinearity motivates caution in interpreting the first order condition as it may introduce unobserved interactions between the multiplied elements of the equation. Still, a cursory discussion of its elements provides some insights regarding the model. Online Appendix A.1 and the calibration analyses corroborate these insights.
and Sydsaeter (1987) for additional methodological details.

### 2.2 Lending and Insurance Decisions

As an update to the model, the lender can buy a sum insured $q_t \geq 0$ at premium rate $p$ and receive a payout based on the function $i(s_{t+1})$ where $s$ describes the severity of the insured disaster. This lender’s problem is now

$$\max_{l_t \geq 0, q_t \geq 0} \sum_{t=1}^{\infty} \delta^t E[\pi_{t+1} - g_{t+1}]$$

subject to,

$$\pi_{t+1} = r_l t - r_f (l_t - K_t) - h_t - \xi_{t+1}(1 + r)l_t - p q_t + q_t i(s_{t+1})$$

$$c_{t+1} = (K_t + \pi_{t+1})/(1 - \xi_{t+1})l_t$$

$$g_{t+1} = \nu \max\{0, \kappa - c_{t+1}\}^2 (1 - \xi_{t+1})l_t$$

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

The first order condition for the insurance decision is

$$V_{q_t} : \ E[(1 + \delta \lambda_t)(\pi_{q_t} - g_{q_t})] \leq 0$$

$$= E\left( (1 + \delta \lambda_t) \left( -p + i(s_{t+1}) - \frac{\partial g_{t+1}}{\partial c_{t+1}} \frac{\partial c_{t+1}}{\partial q_t} \right) \right) \leq 0$$

$$= E\left( (1 + \delta \lambda_t) \left( -p + i(s_{t+1}) - \frac{\partial g_{t+1}}{\partial c_{t+1}} \left( \frac{-p + i(s_{t+1})}{(1 - \xi_{t+1})l_t} \right) \right) \right) \leq 0$$  

(5)

The optimal insuring policy depends on premiums relative to payouts, $-p + i_{t+1}$. It also depends on how the insurance influences the lender’s regulatory capital and associated penalties, $\frac{\partial g_{t+1}}{\partial c_{t+1}} \left( \frac{-p + i(s_{t+1})}{(1 - \xi_{t+1})l_t} \right)$. During a severe disaster (when $i$ is large relative to $p$), the insurance would increase the lender’s capital. However, in non-disaster periods (when $i = 0$), the insurance would reduce the lender’s capital due to paid premiums. Finally, the dynamic nature of the problem again adds the term in the first parentheses, $(1 + \delta \lambda_t)$. In cases where some positive level of insurance is optimal (i.e., $q > 0$), the dynamic setting would tend to increase insurance demand as insuring can alleviate multi-period capital constraints. The optimal lending decision appears the same as Equation (2); however, the optimal loan amount will differ if the lender insures as insuring changes the lenders’ profits and penalties (as shown in Equation 4).
2.3 Background Risk

Here, and for basis risk below, I provide an initial assessment of how background risk affects the insurance decision. Because certain features of the dynamic model complicate a full analytical exposition, I complement this assessment with analyses of the calibrated model in Section 5.

The loan loss rate $\xi$ is the stochastic component of the model and comprises two random variables $x_{t+1} \in \{0, 1\}$, which indicates the occurrence of a disaster, and $\varepsilon_{t+1}$, which describes other non-repayment risks. The loan loss rate follows

$$
\xi(x_{t+1}, \varepsilon_{t+1}) = \varepsilon_{t+1}(\eta, \theta) + \psi x_{t+1}.
$$

(6)

where $\varepsilon$ is lognormally distributed, parameter $\eta$ is the expected loss rate during nondisaster states, $\theta$ is the standard deviation of $\varepsilon$, and $\psi$ is the loss rate if a disaster occurs.\textsuperscript{11} For completeness, I impose the additional constraint that $\xi_{t+1} \in [0, 1]$ where 1 indicates a total loss of the loan portfolio. While the upper constraint is possible theoretically, it is not binding in real-world applications.

Parameter $\theta$ is the measure of background risk such that larger $\theta$ indicates more risk. I discuss its effects on the lending and insurance decisions with an informal application of the envelope theorem. Equation (2) shows the lender’s first order condition with respect to lending amount $l$. Increasing $\theta$ would increase the volatility but not the mean of loan losses and so the effects on income $\pi$ would be neutral. However, background risk would increase the volatility of the lender’s capital ratio and so increase expected penalties $g$ for a given lending amount. The increased risk of penalties would motivate the lender to reduce lending to balance its expected marginal profits and penalties. Background risk may additionally reduce lending in this dynamic setting by affecting the shadow price of equity $\lambda_t$, which captures the effects of capital constraints in future periods. Thus, lending is expected to decrease in background risk.

The effect of background risk on insurance demand is not obvious from its first order condition, Equation (5). When background losses are large, insurance payouts reduce penalties if the disaster occurs, but insurance premiums increase penalties if no disaster occurs. Thus, the magnitude of background risk relative to disaster risk may matter. Also, the joint lending and insurance decision is an important consideration here as each choice affects the risk of penalties. The calibration exercise in the next sections returns to this point.

\textsuperscript{11}I treat the disaster as binary to correspond with the risk assessment data provided by a Peruvian lender (Section 3.1). The lender provided its expected loss if a severe El Niño occurred.
2.4 Basis Risk

Similar to Cummins et al. (2004), Golden et al. (2007), and Chantarat et al. (2013), I model basis risk as an error term $\nu_{t+1}$ in the relationship between the index’s payouts and policyholder losses,

$$i(s_{t+1}) = \begin{cases} 
1 + \nu_{t+1} & \text{if } s_{t+1} \geq \bar{s} \\
0 & \text{o.w.} 
\end{cases} \quad (7)$$

where $s_{t+1} \geq \bar{s}$ is an indication of the disaster. Let $\nu_{t+1}$ be a random variable that is approximately normally distributed with zero mean and variance $\sigma^2$, $\nu \sim N(0, \sigma^2)$. I also impose that $\nu \in [-1, 1]$. The lower bound prevents negative insurance payouts and the upper bound provides symmetry so that all modeled contracts have the same expected value.\(^{12}\) Thus, when a disaster occurs, the expected payout is the sum insured, but $\nu$ creates uncertainty about the actual payout.

Parameter $\sigma$ is the measure of basis risk such that larger $\sigma$ indicates more basis risk. I return to the lender’s first order condition with respect to the sum insured $q$, Equation (5). Because basis risk does not change the insurance contract’s expected value, varying basis risk does not influence the relationship between premiums and expected value ($-p + i(s_{t+1})$) and so its effect on income $\pi$ is neutral. However, basis risk may reduce the optimal level of insurance because the insurance less reliably augments the lender’s capital ratio during disaster states and so increases expected penalties for a given sum insured, captured in the term $\frac{\partial g_{t+1}}{\partial c_{t+1}} \frac{\partial c_{t+1}}{\partial q}$. In sum, basis risk would seem to reduce the optimal sum insured.

How basis risk affects the optimal lending amount depends on the joint lending and insurance decision. If the optimal sum insured is zero, then basis risk does not affect lending. If the lender insures, basis risk would affect the optimal lending decision through increasing the expected penalty since the insurance would sometimes pay less during disasters. The increase in the expected penalty would motivate the lender to lend less to balance expected marginal profits and penalties. The degree to which basis risk affects the optimal insurance and lending amount is unclear and so I additionally examine basis risk in the calibrated model. In the main applied analyses below (Section 4), I focus on other features of the model and assume that basis risk is zero ($\sigma = 0$), but

\(^{12}\)Clarke (2016) models basis risk differently to leverage the model of Doherty and Schlesinger (1990). He considers the special case in which both disasters and payouts are binary, leading to four possible outcomes: no disaster and no insurance payment, disaster and no payment, etc.

The error-term approach following Cummins et al. (2004), Golden et al. (2007), and Chantarat et al. (2013) seems more appropriate in my setting – the El Niño insurance is similar to a nonlinear hedge (e.g., financial option rather than a futures contract) and index triggers are set in such a way that the possibility of a payment in the absence of an event seems small (Section 1). I include an extreme basis risk calibration such that if a disaster occurs, the insurance pays nothing half the time and double the loss half the time. This basis risk calibration has similarities to Clarke’s approach in that an insured lender could experience a disaster but receive no payment.
then vary basis risk in subsequent analyses (Section 5.2).

3 Setting and Calibration

I apply the model to the case of El Niño related flood risk for an SME lender in Peru. The period of study was 2009 to 2012. This section describes the setting and the studied lender, describing the financial performance of the lender, its vulnerability to a disaster, the likelihood of a severe El Niño, and the structure of the El Niño insurance.

Peru is an upper middle income country on the west coast of South America with a population of about 30 million (World Bank, 2017). In the period of study, (and the 2000s and 2010s more generally), Peru enjoyed a robust economy and stable political environment. For example, average GDP growth was 4.1% from 2009 to 2012 (World Bank, 2017).

The northern coastal region of Peru is an important agricultural region of the country, exporting high value commodities such as avocados, grapes, asparagus, and blueberries. It is also vulnerable to El Niño-related flooding. During the period of study, the most recent severe El Niño events had occurred in 1998 and 1983 (another severe El Niño occurred in 2016). Both caused rainfall of roughly 40 times the average for January to April (Skees and Murphy, 2009). While the modeled lender did not hold a large portion of market share in northern Peru in 1998, the community lenders in the region were significantly affected. For example, one renegotiated the loan terms on 3.6 percent of its portfolio to manage loan repayment problems due to the 1998 El Niño (Collier et al., 2011). Online Appendix A.2 provides a case study of a community lender, Caja Trujillo, and the 1998 El Niño, developed through interviews and analyses of its financial records. Caja Trujillo reduced lending after the event to manage its losses on existing loans.

During the period of study, an index insurance product against severe El Niño was introduced and could be purchased by lenders (and other firms) in Peru. A lender considering whether to purchase the insurance provided data on its El Niño exposure for this analysis. The lender surveyed its loan officers in the third quarter of 2012 about the vulnerability of their loans to a severe El Niño. I use monthly income and balance sheet data on the lender provided by the banking supervisory agency in Peru (SBS, 2013). To align with the survey, I use an evaluation period of July 2009 to June 2012, the three years prior to the survey. A severe El Niño event did not occur in this time and so I treat the evaluation period as representative of lending conditions in the nondisaster state. I use publicly available data from the U.S. National Oceanic and Atmospheric Administration NOAA (2013) to estimate the distribution of El Niño risk. The model intends to describe the lender’s
decisions regarding its optimal lending and insurance policies using the information available at the end of 2012.

The modeled lender 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. Like its peers, the lender initially specialized geographically and has expanded from those regional offices.

Table 1 summarizes the model calibration, and I discuss each part below. As a robustness test, I examine an alternative calibration in Section A.5, using the lending rates and operational costs of a larger lender. The results from that alternative specification are qualitatively similar to those using the calibration described here.

Table 1: Calibration summary

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Symbol</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lending interest rate (annual)</td>
<td>$r$</td>
<td>40%</td>
</tr>
<tr>
<td>Risk free rate (annual)</td>
<td>$r_f$</td>
<td>4.25%</td>
</tr>
<tr>
<td>Linear lending expense</td>
<td>$\alpha$</td>
<td>2%</td>
</tr>
<tr>
<td>Quadratic lending expense</td>
<td>$\beta$</td>
<td>0.2%</td>
</tr>
<tr>
<td>Linear equity expense</td>
<td>$\gamma$</td>
<td>10%</td>
</tr>
<tr>
<td>Quadratic equity expense</td>
<td>$\zeta$</td>
<td>0.1%</td>
</tr>
<tr>
<td>Discount rate (annual)</td>
<td>$\delta$</td>
<td>95.75%</td>
</tr>
<tr>
<td>Expected loan loss rate (nondisaster)</td>
<td>$\eta$</td>
<td>3.0%</td>
</tr>
<tr>
<td>Standard deviation of loan loss rate (nondisaster)</td>
<td>$\theta$</td>
<td>0.24%</td>
</tr>
<tr>
<td>Minimum capital requirement</td>
<td>$\kappa$</td>
<td>14%</td>
</tr>
<tr>
<td>Disaster loan loss rate</td>
<td>$\psi$</td>
<td>3.5%</td>
</tr>
<tr>
<td>Disaster probability (annual)</td>
<td>$P[s_{t+1} \geq 24.5\degree]$</td>
<td>4.6%</td>
</tr>
<tr>
<td>Insurance premium (loaded price, % of sum insured)</td>
<td>$p$</td>
<td>8.05%</td>
</tr>
<tr>
<td>Supervisory stringency</td>
<td>$\nu$</td>
<td>5</td>
</tr>
</tbody>
</table>

Note: Values used in model calibration based on the evaluation period July 2009 to June 2012. The table reports annualized values (e.g., interest rates). Values for Rows 1 to 10 are derived from monthly financial statements (Section 3.2). As discussed in Section A.1.1, I assume that operational expenses (Rows 3 to 6) follow $h = \alpha l_t + \beta l_t^2 + \gamma K_t + \zeta K_t^2$. The disaster loan loss rate $\psi$ is from the loan officer survey (Section 3.1). The disaster probability is from an El Niño index measured by NOAA (Section 3.3). Section 3.4 discusses the insurance premium $p$. Supervisory stringency is inferred from model simulations (Section 3.5).

3.1 Loan Officer Survey

The loan officer survey provides the estimate of the disaster-related loan loss rate $\psi$. The lender conducted a survey of all 27 of its credit risk managers and senior loan officers in the vulnerable area regarding their perceived credit exposure to severe El Niño. The area considered vulnerable to El Niño by the lender is the administrative regions of La Libertad, Lambayeque, Piura, and Tumbes. Lending in these regions comprise 20% of its portfolio. 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 lender 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 the experience of similar lenders during the 1998 event (Collier et al., 2011) and the case study of Caja Trujillo in Online Appendix A.2. Online Appendix A.3 provides the survey.

The survey includes an open-ended question asking loan officers how a severe El Niño would affect credit growth. The responses offer a nuanced perspective on the diverse credit risks associated with a severe flood event. For example:

- “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.”

3.2 Financial Statements

I calibrate \{r, r_f, \alpha, \beta, \gamma, \zeta, \delta, \eta, \theta, \kappa\} (Rows 1 to 10 in Table 1) using monthly income and balance sheet data from July 2009 to June 2012. Unless otherwise noted, I use the average value during the study period. For example, the lender’s average annual lending interest rate is 40%, which is consistent with other SME lenders in Peru. The regulating supervisor required community lenders to maintain a capital ratio of at least 14%. I use income statement categories “financial services expenses” and “administrative expenses” to calibrate the lending and equity expenses, respectively. The risk free and discount rates are based on the interbank rate in Peru during

\[13\] The distinction between lending and equity expenses is not important for the analysis, but is a stylization that improves the stability of the model across sensitivity analyses and extensions. I use the average financial services
the evaluation period. The loan loss rate $\xi$ is calibrated using data from the financial statements and loan officer survey. It is the proportion of loans past due for more than 90 days, a common definition of loan default (BCBS, 2006).

### 3.3 Probability of Severe El Niño

El Niño events are caused by a disruption in oceanic and atmospheric circulation along the equatorial Pacific. Severe disruptions cause a massive warm front that results in three to four months of torrential rain and flooding in northern Peru and southern Ecuador (Lagos et al., 2008). Because of the geophysical process, Pacific ocean temperatures are the primary measure of El Niño used by climate scientists (e.g., Wolter and Timlin, 1998). “Niño 1+2” is a monthly measure of ocean temperature 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 with a Pearson correlation of 0.79 and Spearman rank correlation of 0.94. They propose it as an index for El Niño, and it is the index used for the El Niño index insurance product sold in Peru (Skees et al., 2007).

Following the structure of the El Niño insurance, I use the average reported temperatures for Niño 1+2 for November and December as the El Niño index and define a temperature exceeding 24.5°C Celsius on the index as a severe El Niño event. I estimate the probability of severe El Niño using maximum likelihood estimation of the generalized extreme value (GEV) distribution, resulting in GEV location, scale, and shape parameters of 21.861, 0.809, and 0.041, respectively. Figure 1 shows a histogram of the Niño 1+2 index values and the estimated probability density function. The two severe events shown in the right side of the figure resulted in torrential rains in January to April in 1983 and 1998 in northern Peru. Based on this analysis, the estimated annual probability of severe El Niño is 4.6%. Online Appendix A.4 provides additional details on the El Niño data.

### 3.4 El Niño Insurance

The El Niño insurance contracts offered in Peru have a linearly increasing payout structure between a trigger and exhaustion point. 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 the loan officer survey, I treat severe El Niño expense for the lending expenses $\alpha$ and $\beta$ and average administrative expense for the equity expenses $\gamma$ and $\zeta$. Since the period of study is only three years, the data provide little variation for estimating the convexity of operating expenses and so I assume that quadratic lending expense $\beta$ and quadratic equity expense $\zeta$ are one tenth and one hundredth of the linear expense values, respectively (i.e., $\beta = \alpha/10$). The results and conclusions are robust across other operational expense parameterizations.
Niño as a binary event and use a stylized contract such that the full sum insured is paid if an event occurs, Equation 7, setting the trigger at $\bar{s} = 24.5^\circ$. In the main analyses (Section 4), I assume that the contract has negligible basis risk to focus on other features of the model, but extend the model to examine basis risk in Section 5.

Based on analyses of the price of El Niño insurance and Peru and discussions of this product with several insurers and reinsurers, I estimate a premium loading of approximately 75% of the actuarially fair rate due to loads for administrative and capital costs. The loading is consistent with previous estimates for catastrophe insurance (e.g., Cummins and Mahul, 2009). The loading results in an annual premium rate of 8.05% of the sum insured for the loaded, stylized contract, a rate similar to the contracts offered in Peru, which range from approximately 7 to 11% of the sum insured.\footnote{Please see The Economist (2014) and GlobalAgRisk (2013) for more information on El Niño insurance.}

### 3.5 Simulations, Summary Statistics, and Supervisory Stringency

I use simulations of the evaluation period to analyze model performance and estimate the supervisory stringency parameter $\nu$ as this parameter is not directly observed. I compare model
performance with the actual performance of the lender during the evaluation period of July 2009 to June 2012 through Monte Carlo simulations. The adverse effects of El Niño occur over a period of roughly three months in Peru and so I calibrate the model for quarters (i.e., each period is three months long). Each simulation draw is 12 quarters in length. I run 100,000 draws, recording the means, standard deviations, minima, and maxima for several income and balance sheet indicators.

As the modeled lender is vulnerable to severe El Niño, its optimal lending policy will account for this risk. However, a severe El Niño did not occur during the evaluation period and so I do not allow for El Niño during these simulations, set $x_{t+1} = 0$ in Equation (6), to facilitate comparisons to the evaluation period. Stochastic performance is driven by the unexplained variation in loan losses $\varepsilon_{t+1}$. Also, as the lender had not considered the recently offered El Niño insurance, I model the lender’s only decision as its lending allocations, following the lender’s problem outlined in Equation (1).

Table 2 provides the results. Loan defaults are quite close in the simulation to the calibration period based on construction as I estimate $\varepsilon$ in Equation (6) using the lender’s defaults. Lending revenues and administrative costs are similar across the empirical and simulation results; however, the simulations underestimate their volatility as the model does not include stochastic components besides loan losses.

Regarding the capital ratio, the lenders holds a capital buffer in excess of the 14% regulatory requirement. The mean capital ratio is 15.8% for the lender during the evaluation period, 1.8 percentage points above the regulatory requirement. The simulation also results in a mean capital ratio of 15.8% when the supervisory stringency parameter $\nu = 5$. Greater stringency (larger $\nu$) results in a larger buffer and vice versa. Section 5.3 provides a sensitivity test for this parameter and discusses policy implications of supervisory stringency. The capital buffer also depends on background risk, and it is possible that observations of loan losses during the evaluation period do not accurately describe this risk. Section 5.1 examines other calibrations of background risk and their effects on the lender’s capital buffer and insurance decisions. The larger standard deviation for the empirical capital ratio is due to lumpy dividend payments, which tend to occur annually. Smoothing these payments across quarters reduces the empirical standard deviation to 0.3 and so aligns well with the simulation value of 0.2.
Table 2: Empirical and simulated performance of the studied lender, annualized values (%)

<table>
<thead>
<tr>
<th></th>
<th>Empirical</th>
<th></th>
<th></th>
<th>Simulated</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>St. Dev.</td>
<td>[Min, Max]</td>
<td>Mean</td>
<td>St. Dev.</td>
<td>[Min, Max]</td>
</tr>
<tr>
<td>Defaults/loans</td>
<td>3.0</td>
<td>0.2</td>
<td>[2.4, 3.3]</td>
<td>3.0</td>
<td>0.2</td>
<td>[2.7, 3.4]</td>
</tr>
<tr>
<td>Lending revenues/loans</td>
<td>34.2</td>
<td>1.3</td>
<td>[31.0, 36.9]</td>
<td>34.1</td>
<td>0.1</td>
<td>[33.9, 34.2]</td>
</tr>
<tr>
<td>Administrative costs/loans</td>
<td>15.8</td>
<td>1.2</td>
<td>[13.8, 18.3]</td>
<td>18.5</td>
<td>0.01</td>
<td>[18.4, 18.7]</td>
</tr>
<tr>
<td>Capital ratio</td>
<td>15.8</td>
<td>1.5</td>
<td>[13.1, 18.9]</td>
<td>15.7</td>
<td>0.2</td>
<td>[15.4, 16.1]</td>
</tr>
</tbody>
</table>

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 from Monte Carlo simulations with stochastic loan performance of the evaluation period with 100,000 draws.

4 Results

This section examines the optimal lending and insuring decisions. I begin with the model without insurance as a reference and examine the optimal lending decision and the effects of a disaster in this setting. Then, I consider the model in which the lender may also insure its disaster risk. I examine the lender’s optimal insurance coverage, how insuring affects the optimal lending decisions, and the effects of a disaster in this setting.

4.1 Credit Model

4.1.1 Optimal Policy

This section examines the lending decisions of the modeled lender, following the model from Section 2.1. Panel A of Figure 2 shows the optimal lending policy. The first graph shows the optimal policy as a function of the equity state. The second figure shows the corresponding expected capital ratio emerging from the lending decision. For reference in the first figure, the cross-hair shows the optimal lending amount when equity is at the mean of its non-disaster steady state distribution (the amount of equity toward which the model converges). Equity is 0.8, loan origination is 5.4, and the expected capital ratio is 15.8 percent.

The figure shows two kinks in the optimal policy. When equity is small (below 0.7), operational costs are small and so returns on lending are high. The lender operates below minimum capital requirements (of 14%), and the resulting regulatory penalties limit lending. The slope of the optimal policy in this range is about 6.5; a dollar increase in equity increases loan origination by 6.5 dollars. As equity grows, operational costs increase increase in equity. Between equity values of 0.7 and 1, the lender’s expected capital ratio is above minimum requirements; however, the capital ratio will fall below the minimum if the disaster occurs. The dot-dash line (in green) in the second
figure shows the capital needed to prevent the lender from falling below minimum requirements in the event of a disaster – a disaster results in loan losses of 3.5% and so this line is at 17.5%, 3.5 percentage points above minimum requirements. In this range, the slope of the optimal lending policy in the first graph is about 3. Above equity values of 1, the lender’s capital ratio is sufficiently high that it does not fall below minimum requirements if a disaster occurs. Around equity of 1.1, expected marginal revenues equal expected marginal costs and the slope of the optimal policy is 0; increases in equity no longer increase loan origination.

4.1.2 Disaster Simulation

Disaster simulations show lending reductions following an event due to capital constraints. The solid line in Panel B of Figure 2 illustrates model results for a disaster simulation. In the figure, the disaster occurs in Period 0. Eight quarters precede it; 20 follow. The initial value of equity is set at the mean of its non-disaster steady state distribution, and the y axes for equity and loans are shown as a percent of the mean values of their non-disaster steady state distributions. The capital ratio penalty is scaled using average steady state revenue. To isolate the effect of the disaster in the simulation, I set the unexplained variation in loan losses from Equation (6) equal to its mean and show the 95% confidence intervals for each period as dotted gray lines. Thus, the solid line shows the expected effect of a disaster, and the confidence intervals show the degree to which the effect in a single period is likely to fluctuate due to background risk.

The seemingly small loss of 3.5% of the loan portfolio represents 26% of the lender’s equity. This decline pushes the capital ratio below minimum requirements and results in a penalty of about 2% of the period’s revenues. In response, the lender contracts credit by 16% 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 the regulatory minimum, credit contraction occurs.

4.2 Model with Insurance

This section examines the lending and insurance decisions of the modeled lender, following the model from Section 2.2. I consider two cases. The first is one in which the insurance is sold at the actuarially fair price (i.e., the premium equals the expected payout). In the second case, the insurance product is priced at the loaded rate observed in the Peruvian market. The actuarially
Figure 2: Optimal policy and disaster simulation

Note: Panel A shows the optimal lending policy and the resulting expected capital ratio. The cross-hairs identify the mean values for the non-disaster steady state. Panel B shows a disaster simulation. The solid line identifies the expected performance of the modeled lender given the occurrence of the disaster; the dotted lines provide a 95% confidence interval for background risk, indicating the degree to which other factors affecting loan losses are likely to influence performance in a single period. The y axes for equity and loans are scaled based on the mean values of their non-disaster steady state distributions. The y axis for the penalty is written as a percent of average steady state revenue.

Fair insurance provides a helpful reference for the loaded insurance, but it may also be of interest in its own right. For example, a public program might decide to offer index-based disaster insurance at the actuarially fair rate. Also, a bank holding company might use the actuarially fair price to
guide internal capital transfers within the company, a point I discuss further below.

4.2.1 Optimal Policy

Panel A of Figure 3 shows the optimal insurance and lending policies. The dot-dashed purple line shows the optimal policies for the actuarially fair insurance, and the dashed green line for the loaded insurance. The lender with actuarially fair insurance fully insures the disaster exposure. Thus, the level of insurance is increasing until the lender stops originating additional loans, around an equity level of 0.9. The lender with loaded insurance transfers about half of the disaster exposure up to equity of 0.8, the mean of the non-disaster steady state. Above this point, the lender originates fewer loans and retains an increasing portion of the risk as its capital reserves are sufficient to protect it from a severe event. With sufficiently large capital reserves, it no longer purchases the loaded insurance.

Insurance increases the optimal lending amount in the vicinity of the steady state. The second row of Panel A illustrates the effect. The solid blue line replicates the optimal lending policy described in Section 4.1.1. Insurance motivates the lender to lend more per unit of equity and so operate with a lower internal capital target. The lender that retains its risk operates with a target capital ratio of 15.8%, the lender with actuarially fair insurance targets 14.3%, and the lender with loaded insurance targets a capital ratio of 14.8%. Consequently, the lender with actuarially fair insurance increases lending by 8% during non-disaster conditions, 5% in the loaded case, relative to the uninsured lender.

4.2.2 Disaster Simulation

Panel B shows that transferring disaster risk reduces credit contraction following disasters. When the disaster occurs, the insurance payout offsets loan losses and so smooths lender income, protecting its equity, and stabilizing the capital ratio. The lender retaining its risk contracts credit by 16% of its pre-event level, the lender with loaded insurance by 10% of its pre-event level, and the lender with actuarially fair insurance lends at effectively the same rate.\(^{15}\)

While the focus of this research is autonomous SME lenders, these results are also potentially relevant to bank holding companies. A commonly recognized challenge of internal capital markets is asymmetric information within the family of organizations. (Stein, 1997, 2002). For example, a parent company cannot always determine whether a subsidiary needs a capital infusion because of bad luck or bad management. Rather than using external insurance markets, bank holding companies might formally integrate disaster-contingent claims in their internal capital markets. The parent and subsidiary would enter a contract that transfers capital to the subsidiary based on an observable measure of the disaster. 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. Thus, the modeled lender with actuarially fair insurance in Figure 3 would seem to fit this scenario.
Section A.5 provides an alternative calibration as robustness. That calibration reflects the lower SME lending rates and operational costs of a larger lender. Among other differences, larger lenders in Peru tend to serve larger, more sophisticated SMEs in urban environments, which reduces their operational costs. The results using this alternative calibration are qualitatively similar to those of the main text: insuring increases the \textit{ex ante} credit supply and reduces \textit{ex post} credit contraction, the uninsured FI manages its disaster risk using a capital buffer above regulatory requirements, the optimal sum insured with the loaded insurance is about half that for the actuarially fair insurance, etc., and so support the main findings described in this section\footnote{The rates for the larger lender may also reflect those of the studied lender in the coming years as its operating costs have substantially declined since 2001. An additional insight from this analysis is that the larger profit margins of the insured modeled lender speed its recovery through retained earnings. The smaller margins of the larger lender result in a slower recovery and so increase the benefits of insuring. For example, the loaded insurance is expected to increase access to credit by 8% for the larger insurer versus 5% for the modeled insurer.}

5 Background Risk, Basis Risk, and Supervisory Stringency

This section includes three extensions of the model, which provide additional insights and serve as sensitivity analyses. The first two examine how changes in background risk and basis risk, respectively affect the optimal insurance policy. The third examines supervisory stringency as measured by the penalty on regulatory capital.

5.1 Background Risk

I examine how changes in background risk affect the optimal level of insurance, holding all parameters constant. Peru presented a stable economic and political environment during the period of study that resulted in little observed background risk for the modeled lender; however, background risk may be much larger in other settings, especially in the developing world.

As described in Section 2.3, the loan non-repayment rate $\xi$ depends on two random variables: the occurrence of a disaster $x \in \{0, 1\}$ and all other unexplained variation $\varepsilon$, which has a mean $\eta$ and standard deviation $\theta$,

$$\xi(x_{t+1}, \varepsilon_{t+1}) = \psi x_{t+1} + \varepsilon_{t+1}(\eta, \theta). \tag{8}$$

Parameter $\psi$ is the loan loss rate if a disaster occurs. The causes of this unexplained variation are immaterial for this research, but possibilities include macroeconomic volatility, exchange rate risk, and commodity price risk.
Figure 3: Optimal policy and disaster simulation, insured and uninsured cases

Note: Figures include three cases: the lender 1) retains its risk, 2) insures at the actuarially fair rate, and 3) insures at the actuarially unfair, loaded rate observed in the El Niño insurance market. Panel A shows the optimal insuring and lending policies and the resulting expected capital ratio. Panel B provides an illustrative disaster simulation. The vertical axes are scaled to the mean value of the non-disaster steady state distribution for the lender that retains its risk.

I measure background risk as the standard deviation $\theta$ of the unexplained portion of loan non-repayment $\varepsilon$. I scale background risk to facilitate comparisons with the natural disaster risk in the sensitivity analysis. Let $CI^+$ equal the upper bound of the 95 percent confidence interval of $\varepsilon$. I
Figure 4: Background risk and the optimal insurance policy

Note: Figures show the optimal insurance coverage, for the loaded insurance, and target capital ratio across varying levels of background risk. The cross-hairs identify the mean values for the non-disaster steady state. Let $CI^+$ equal the upper bound of the 95 percent confidence interval of $\varepsilon$. $CI^+ = \eta + j\psi$ where $j \in \{0, 50\%, 75\%, 100\%, 125\%\}$ across sensitivity tests, $\eta$ is mean loan non-repayment (3%), and $\psi$ is the disaster non-repayment (3.5%). Thus, $j$ describes the size of a background shock relative to the disaster.

vary $\theta$ such that $CI^+ = \eta + j\psi$ where $j \in \{0, 50\%, 75\%, 100\%, 125\%\}$ across sensitivity tests, $\eta$ is mean loan non-repayment (3%), and $\psi$ is the disaster non-repayment (3.5%). Thus, $j$ describes the size of a background shock relative to the disaster. For example, when $j = 100\%$, the 97.5 percentile of $\varepsilon$ is 6.5% and so represents a 3.5 percentage point increase above the mean loan non-repayment, which equals the disaster non-repayment rate.

Figure 4 shows the optimal insuring policy for the loaded insurance. The first image is the optimal insurance policy and the cross-hairs identify the mean value of the non-disaster steady state. The optimal level of disaster insurance is decreasing in the background risk. At the steady state, the lender stops purchasing the loaded disaster insurance when the upper confidence interval of the background risk equals 75% of losses from the disaster.

The second image shows the target capital ratio. Background risk increases the lender’s target capital ratio. This capital buffer is a form of self-insurance against the background risk, but also protects the lender when a disaster occurs. As a result, this buffer reduces the benefits of insuring the disaster risk. At around 17.5%, the capital buffer is sufficiently large that the lender can incur the estimated disaster loss of 3.5 percentage points without falling below regulatory requirements of 14%. Thus, the analysis shows that the value of disaster insurance is substantially reduced for settings in which the disaster risk is not large relative to the other risks faced by the lender.
5.2 Basis Risk

As described in Section 5.2, I model basis risk as $v$ in the payout function

$$i(s_{t+1}) = \begin{cases} 1 + v_{t+1}(\sigma) & \text{if } s_{t+1} \geq \bar{s} \\ 0 & \text{o.w.} \end{cases}$$

where $s_{t+1} \geq \bar{s}$ is an indication of the disaster. Let $v_{t+1}$ be a random variable that is approximately normally distributed with zero mean and variance $\sigma^2$, $v \sim N(0, \sigma^2)$. I also impose that $v \in [-1, 1]$. The upper bound provides symmetry so that all modeled contracts have the same expected value.

The measure of basis risk is $\sigma$. I conduct sensitivity analyses by varying $\sigma \in \{0, 0.25, 0.5, 1, 100\}$. Figure 5 shows the optimal insurance coverage for the loaded insurance across the sensitivity analyses. The model in Section 4 implicitly assumes that the contract does not include basis risk, i.e., $\sigma = 0$, and so the top line in the first figure replicates its results. The sum insured is declining in basis risk. When $\sigma = 1$, insurance does not pay about one sixth of the time that a disaster occurs and, about one sixth of the time, pays an amount twice as large as the actual magnitude of the disaster. The lowest line shows $\sigma = 100$. In this extreme case, the insurance pays nothing half of the time that a disaster occurs, and twice the actual magnitude half of the time. Compared to the model without basis risk, $\sigma = 100$ reduces the optimal sum insured by about half. The second image shows the effect of basis risk on lender leverage. Basis risk increases the lender’s target capital ratio as the lender retains more and insures less of the risk. This larger capital buffer reduces the amount of credit supplied per unit of equity.

Thus, this extension shows a tendency for the lender to continue to insure a portion of its disaster exposure despite basis risk. While the setting differs substantially, this result is in the spirit of Cummins et al. (2004) who find that index-based risk transfer may allow insurers to manage Florida hurricane risk effectively, even when basis risk is large.

5.3 Supervisory Stringency and Ex Post Lending

This section examines the effect of the regulatory capital penalty on lending. The analysis provides a sensitivity test as supervisory stringency is not observed directly. Also, it provides insights regarding how modifying the severity of the penalty may affect the ex ante and ex post credit supply. As described in Section 2.1, the lender must keep its capital ratio $c$ above a regulatory
Strengthening Local Credit Markets

minimum $\kappa$, or it will incur a penalty $g$. The penalty function is

$$
g_{t+1} = \begin{cases} 
\nu (\kappa - c_{t+1})^2 (1 - \xi_{t+1}) l_t & \text{if } c_{t+1} < \kappa \\
0 & \text{o.w.}
\end{cases}
$$

where $\nu$ is a parameter describing the severity of the penalty. In the analyses in Section 4, $\nu = 5$. Across sensitivity analyses here, I consider $\nu \in \{0.1, 1, 10, 100\}$.

Figure 6 shows the effect of regulatory stringency on lending and the capital ratio in a disaster simulation. The lender begins each simulation with the mean of its non-disaster steady state equity. The lender with the smallest modeled penalty, $\nu = 0.01$, targets a capital ratio near the regulatory minimum. This lender lends the most ex ante. When the disaster occurs, its capital falls the lowest. The lender operates below the regulatory minimum for several periods, and its credit supply recovers more quickly than the other lenders. In contrast, the lender with the largest penalty, $\nu = 100$, maintains a higher target capital ratio and so lends the least ex post. When the disaster occurs, this lender contracts credit the most. Its capital ratio returns to approximately its target level in the period following the disaster, but its credit supply takes the longest to recover.

This analysis suggests a public policy tradeoff. More lenient supervision can expand the ex ante and ex post credit supply, which are important goals in developing and emerging economies. However, more lenient supervision may reduce lenders’ soundness such that the likelihood of insolvency following a catastrophe increases. Additionally, stringent supervision motivates a rapid response

Note: Figures show the optimal insurance coverage, for the loaded insurance, and target capital ratio across varying levels of basis risk. The cross-hairs identify the mean values for the non-disaster steady state. When the disaster occurs, let $i = 1 + \upsilon$ describe insurance payouts (to be multiplied by sum insured $q$), where $\upsilon \sim N(0, \sigma^2)$ and $\upsilon \in [-1, 1]$. The sensitivity tests vary $\sigma \in \{0, 0.25, 0.5, 1, 100\}$. For example, when $\sigma = 1$, the insurance does not pay about one sixth of the time that a disaster occurs and, about one sixth of the time, pays an amount twice as large as the actual magnitude of the disaster.
from the lender to a falling capital ratio, which seems particularly important for supervisors who have imperfect information regarding portfolio quality.

While it is tempting to consider a policy that relaxes regulatory requirements during disaster periods, such an approach may have unintended side-effects of undermining lenders’ incentives to manage disaster risks and so increase the likelihood of insolvency. Instead, in settings where disaster risk is large relative to background risk, regulators might make regulatory capital requirements more flexible \textit{ex ante} to account for whether lenders are transferring disaster risks. This change would allow for more economic considerations between self-insuring and transferring disaster risk.\footnote{Large banks use their internal capital models to manage risk in this way, which is outlined in the Basel Accords (BCBS, 2011); however, those methods tend to be beyond the modeling sophistication of most developing and emerging market lenders (BCBS, 2010).}

**Figure 6: Supervisory stringency, capital targets, and lending**  
Note: Figures show how supervisory stringency affects lending and the lender’s target capital ratio during a disaster simulation. More stringent supervision is operationalized as higher levels of \( \nu \), and the analyses compare \( \nu \in \{0.1, 1, 10, 100\} \).

### 6 Discussion

Lender-level risk transfer contracts for natural disasters, such as El Niño index insurance in Peru, show promise regarding strengthening local credit markets. Modeling a representative SME lender in Peru, I find that insuring El Niño risk may improve its performance by allowing it to operate with a lower target capital ratio, more fully leveraging its equity. The model suggests that the insurance would increase the lender’s \textit{ex ante} credit supply by about 5% and reduce credit contraction following a disaster.

In sensitivity analyses, I find that while basis risk reduces the optimal insurance coverage,
disaster insurance still benefits the lender when basis risk is large. In contrast, large background risk reduces the modeled lender’s incentives to insure because background risk motivates the lender to target a higher capital ratio. This additional capital self-insures the lender during the disaster, as well. These findings suggest that the magnitude of background risk is an important consideration in determining the viability of a potential lender-level disaster insurance market.

Future research might extend the current analyses in several ways. First, useful insights may emerge from incorporating the features of other disaster risks and credit markets in the model. Second, while this research has focused on lenders, the principles may also be relevant to other large firms that provide services to households and SMEs such as agricultural exporters. Transferring the disaster risk of those large firms might also contribute to reducing the consequences of catastrophes. Finally, extending this research to consider how lender-level disaster insurance might directly facilitate the development of household and SME insurance markets is of utmost importance.

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A Online Appendix

This online appendix provides additional analysis of the theoretical model (Section A.1), a case study of the severe El Niño of 1998 (Section A.2), the loan officer survey (Section A.3), and additional details of the model calibration (Section A.4).

A.1 Theoretical Models: Additional Analysis

This section provides additional analysis of the theoretical model. I begin with a model with two assumptions that differ from the version presented in Section 2: (1) equity financing is frictionless – the lender can raise additional equity each period – and (2) the lender can fully diversify its disaster risks. I then modify these assumptions. These analyses clarify their effects and so provide additional insights on the model. For ease of exposition, I present all details of the model here, repeating some material from Section 2.

A.1.1 Lending with Access to Capital Markets

A representative lender maximizes its expected, discounted stream of returns over an infinite horizon. It begins each period with a stock of equity shares $K_t$ and has access to equity capital markets. Each period, the lender divests its equity shares $K_t$ and issues new ones $k_t$. The lender can originate one-period loans $l_t$ at an interest rate $r$ or invest in other FIs and receive a risk free return $r_f$. Some borrowers do not repay each period due to production risks, but diversification allows the lender to experience a fixed non-repayment rate $\bar{\xi} \in [0,1]$. The lender can also choose to lend more than its newly issued equity $k_t$ by borrowing at the risk free rate.

---

18 Thus, throughout the model, I adopt the convention for loans and equity that lower case $l$ and $k$ describe choice variables and upper case $K$ describes a state variable.

19 This model is intended to be flexible so that the first order conditions below could be used to identify interest rates via the market’s inverse supply equation, or this interest rate could be set following Stiglitz and Weiss (1981). 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.
Additionally, the lender incurs operational costs $h(k_t, l_t)$. Some are a function of its equity ($k_t$), overhead costs such as back-office labor and real estate costs, taxes, bank licensing and regulatory fees, etc. Other costs are a function of its lending decisions ($l_t$) such as origination and monitoring costs. These costs are separable, increasing, and convex ($\partial h_t / \partial k_t, \partial^2 h_t / \partial k_t^2, \partial h_t / \partial l_t, \partial^2 h_t / \partial l_t^2 > 0$). Thus, its income function is

$$\pi_{t+1} = rl_t - rf d_t - h_t - \bar{\xi}(1 + r)l_t$$

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.

The lender is monitored by its capital ratio,

$$c_{t+1} = \frac{k_t + \pi_{t+1}}{(1 - \bar{\xi})l_t}$$

Thus, the capital ratio is evaluated after the lender has realized any returns from the period such that its capital is represented by initial equity and current income (or losses) and the value of its loan portfolio is adjusted to account for non-repayment. If the capital ratio falls below the minimum requirement $\kappa$, the supervisor responds with increasingly invasive penalties. This penalty is

$$g_{t+1} = \begin{cases} 
\nu(\kappa - c_{t+1})^2(1 - \bar{\xi})l_t & \text{if } \kappa > c_{t+1} \\
0 & \text{o.w.}
\end{cases}$$

The penalty is increasing in the amount that the capital ratio falls below minimum requirements and is scaled based on the size of the lender, as measured by outstanding loans. Financial gains or losses are transferred to equity holders the following period

$$K_{t+1} = k_t + \pi_{t+1} - g_{t+1}.$$  

In sum, the lender solves the problem

$$\max_{l_t \geq 0, k_t \geq 0} \sum_{t=1}^{\infty} \delta^t (\pi_{t+1} - g_{t+1})$$  

I model operational costs as $h(k_t, l_t) = \alpha l_t + \beta l_t^2 + \gamma k_t + \zeta k_t^2$ in the numerical analyses in Section 3. While assuming that costs are convex in loans is sufficient to solve the dynamic model, assuming that costs are convex in both loans and equity improves the stability of the numerical analysis. Model results are qualitatively consistent under both sets of assumptions; however, the latter assumption facilitates model extensions and robustness tests in Section 5.

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 3. Generalizing the model to unregulated lenders is straightforward as 1) potential investors and credit rating agencies frequently evaluate unregulated SME lenders by their capital ratios, and 2) lender solvency (i.e., positive equity) is a specific, universal minimum capital requirement.
where \( \delta \) is the discount rate. Equation (9) simplifies to a single-period problem. The lender’s first order conditions are

\[
V_{lt} : \quad r - r_f - h_{lt} - \bar{\xi}(1 + r) - \begin{cases} 
    g_{lt} & \text{if } \kappa > c_{t+1} \\
    0 & \text{o.w.}
\end{cases} \leq 0 \tag{10}
\]

\[
V_{kt} : \quad r_f - \begin{cases} 
    g_{kt} & \text{if } \kappa > c_{t+1} \\
    0 & \text{o.w.}
\end{cases} \leq h_{kt} \tag{11}
\]

where \( V_l \) is the lender’s value function and \( V_t \equiv \partial V_l / \partial l_t \). The first order condition with respect to lending serves as a baseline case for iterations of the model below. Returns to lending are linear, but lending expenses are convex due to operational costs \( h_t \) and regulatory penalties \( g_{t+1} \). If \( l_t > 0 \), then \( V_{lt} = 0 \) and so the optimal lending policy equates lending returns with lending expenses.

Regarding \( V_{kt} \), increasing equity decreases the regulatory penalty, \( g_{kt} < 0 \), and so (11) shows the familiar result that functioning capital markets allow the lender to select a composition of debt and equity that minimizes its financing costs.

### A.1.2 Lender with Access to Capital markets, Holding Undiversifiable Risk

Consider a second case in which the lender is similar in every way except that its borrower’s production risks are undiversifiable due to a large natural disaster exposure, leading to an exogenous, random, independent and identically distributed nonrepayment rate \( \xi_{t+1} \in [0, 1] \) where \( E[\xi_{t+1}] = \bar{\xi} \). This lender’s problem is

\[
\max_{l_t \geq 0, k_t \geq 0} \sum_{t=1}^{\infty} \delta^t E[\pi_{t+1} - g_{t+1}]
\]

s.t., \( \pi_{t+1} = r l_t - r_f (l_t - k_t) - h_t (k_t, l_t) - \bar{\xi}(1 + r) l_t \)

\[
c_{t+1} = (k_t + \pi_{t+1}) / ((1 - \xi_{t+1}) l_t)
\]

\[
g_{t+1} = \nu \max \{0, \kappa - c_{t+1}\}^2 (1 - \xi_{t+1}) l_t
\]

\[
K_{t+1} = k_t + \pi_{t+1} - g_{t+1}
\]
where text in red highlights differences from the previous version of the model. The problem again leads to a single-period one with first order conditions

\[ V_l : \quad r - r_f - h_{lt} - E[\xi_{t+1}](1 + r) - E[g_{lt}] \leq 0 \] 
\[ V_k : \quad r_f - E[g_{kt}] \leq h_{kt}. \] 

These first order conditions show that the lender’s optimal policies employ risk-based capital management – the possibility of falling below minimum requirements changes lender equity and loan allocations. It motivates the lender to lend less and hold more equity than it would otherwise. The convexity of the minimum capital penalty means that this penalty has a larger effect on lending in this stochastic case than in the baseline case, Equation (10), due to Jensen’s inequality. If the penalty \( g \) is positive in any realizations of the disaster (i.e., if it is possible for the disaster to cause the lender’s capital ratio to fall below the minimum requirement), the change in the expected penalty from an increase in lending \( \frac{\partial E[g(\xi_{t+1})]}{\partial l_t} \), in Equation (12), is greater than the change in the penalty from an increase in lending when the loss is determined \( \frac{\partial g(E[\xi_{t+1}])}{\partial l_t} \), in Equation (10). Thus, the lender in this case lends less than the amount in the baseline case where nonrepayment is constant. The same logic holds for equity. Thus, undiversifiable risk reduces lending due to capital management, even when lenders operate above minimum requirements.

Finally, consider a disaster-exposed lender that does not have access to capital markets, the case considered in the body of the paper. While the lender in the previous models divests its equity shares and issues the amount of equity it needs each period, here the lender is endowed with an initial level of equity, retains all earnings (rather than divesting), and cannot raise additional equity. Consequently, from the above, I replace decision variable \( k_t \) with state variable \( K_t \). This lender’s problem is

\[
\begin{align*}
\max_{l \geq 0} & \sum_{t=1}^{\infty} \delta^t E[\pi_{t+1} - g_{t+1}] \\
\text{s.t.,} & \quad \pi_{t+1} = rl_t - r_f(l_t - K_t) - h_t - \xi_{t+1}(1 + r)l_t \\
& \quad c_{t+1} = (K_t + \pi_{t+1})/((1 - \xi_{t+1})l_t) \\
& \quad g_{t+1} = \nu \max \{0, \kappa - c_{t+1}\}^2 (1 - \xi_{t+1})l_t \\
& \quad K_{t+1} = K_t + \pi_{t+1} - g_{t+1}.
\end{align*}
\]
This is a dynamic problem that leads to the first-order condition

\[ V_t : E[ (1 + \delta \lambda_t) (\pi_t - g_t) ] \leq 0 \]

\[ = E[ (1 + \delta \lambda_t) (r - r_f - h_t - \xi_t + 1 (1 + r) - g_t) ] \leq 0 \]  

(13)

where \( \lambda_t \) is the shadow price of equity capital.\(^{22}\) Thus, in the previous iteration of the model, before the introduction of equity market frictions, the optimal lending policy balances expected profits and penalties, \( E[\pi_t - g_t] \) (Equation 12); here, the lender’s optimal lending policy also considers the possibility that loan losses will constrain its ability to lend in future periods, captured in the shadow price of equity capital (\( \lambda_t \)), which further reduces the optimal loan amount.

A.2 Case Study: Caja Trujillo and the 1998 El Niño

Caja Trujillo was the largest MSME lender in its region and provided over 60% of all credit from regulated FIs. Figure 7 compares the percent change in loan allocations from commercial banks to those of Caja Trujillo. Commercial banks tended to lend 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. This increased credit gap remained until approximately May 1999, roughly a year after the torrential rains ended. I examine regional loan allocations for commercial banks then conduct an in-depth analysis of Caja Trujillo.

Figure 8 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

\[^{22}\text{Deriving the first order condition may be facilitated by formulating the lender’s problem as a Bellman equation, } \max_{t \geq 0} V(K_t) = E[\pi_{t+1}(K_t, l_t) - g_{t+1}(K_t, l_t) + \delta V(K_{t+1})]. \text{ The first order condition is} \]

\[ V_t : E[\pi_{t+1,t} - g_{t+1,t} + \delta \lambda_t K_{t+1,t}] \leq 0 \]

\[ = E[\pi_{t+1,t} - g_{t+1,t} + \delta \lambda_t (\pi_{t+1,t} - g_{t+1,t})] \leq 0 \]

where \( \lambda_t \equiv V_{K_{t+1}} \).
Figure 7: Loans from commercial banks and Caja Trujillo in La Libertad

Note: Following El Niño, commercial banks expanded credit by approximately 25% in the state of La Libertad to meet the needs of its customers, mostly large firms. In contrast, capital management related to loan losses challenged the ability of the largest community lender, 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.

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.

Table 3: 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><strong>Total</strong></td>
<td><strong>12,394,358</strong></td>
<td><strong>205,730</strong></td>
</tr>
</tbody>
</table>

Source: Values use 1998 U.S. dollars. 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.

Caja Trujillo is the largest MSME lender in La Libertad, which is 550 km north of Lima on the
Figure 8: 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.

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 9 shows 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.
Figure 9: 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).

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 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.

**A.3 Loan Officer Survey**

The following questions comprise the loan officer survey (translated from Spanish)

1. From the region where the office is located, what economic sector do you consider most vulnerable to El Niño? Please indicate in order of priority.

2. From the sectors identified in the previous question, provide your expectations regarding the levels of active loans, past due loans, and lost loans in the portfolio for the year 2013. Provide only your expectations, expressed as a percentage.

3. Being more specific and only considering the effect on the quality of loan portfolio of the sectors identified in Question 1. Indicate the expected percentage of clients that would not pay their credit in the event of an El Niño (express in percentage).

4. Considering the impact on the commercial sector, what is your expectation of the effect on the levels of active loans, past due loans, and lost loans in the portfolio for the commercial sector?

5. Management is concerned with the potential of a severe El Niño. Would it slow growth for the following year? Explain.

**A.4 Calibration: Additional Details**

NOAA measures Niño 1+2 using a combination of data from ocean buoys, satellite sensors, and transocean liners. Data are available from 1950 (NOAA, 2013); 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.4 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.

![Niño 1+2 Index](https://example.com/nino12.png)

Figure 10: 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.

A.5 Calibration for a Larger Lender

This section provides an alternative model calibration as a robustness test. This calibration reflects the lower SME lending rates and operational costs of a larger lender in Peru. Larger lenders in Peru tend to serve larger, more sophisticated SMEs in urban environments, which reduces their operational costs. This calibration might also reflect the future performance of the studied lender as its lending rates and operational costs continue to decline. For example, during the period of study (2009 to 2012), the average annual lending rate was 40% and administrative costs were 16%, but these rates were respectively 53% and 23% in the period 2001 to 2004. Such changes across time can emerge through technological adoption, increased efficiency, and specialization. Thus, the rates for the larger lender may also reflect those of the studied lender in the coming years. The calibration should be understood as a stylization primarily in the interest of testing the sensitivity...
of the main results to alternative specifications.

Table 4 shows the new values used in this calibration and the original values used in the main analysis (Section 4). The new values include a lower lending interest rate (23%), lower risk free rate (3%), lower lending expenses (0.2% and 0.02%), lower linear equity expense (2%), and higher discount rate (97%). I use the risk assessment details of the studied lender (Section 3.1) and retain other parameter values to facilitate comparisons with the main results.

Table 4: Calibration summary

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Symbol</th>
<th>New Value</th>
<th>Original Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 Lending interest rate (annual)</td>
<td>$r$</td>
<td>23%</td>
<td>40%</td>
</tr>
<tr>
<td>2 Risk free rate (annual)</td>
<td>$r_f$</td>
<td>3%</td>
<td>4.25%</td>
</tr>
<tr>
<td>3 Linear lending expense</td>
<td>$\alpha$</td>
<td>0.2%</td>
<td>2%</td>
</tr>
<tr>
<td>4 Quadratic lending expense</td>
<td>$\beta$</td>
<td>0.02%</td>
<td>0.2%</td>
</tr>
<tr>
<td>5 Linear equity expense</td>
<td>$\gamma$</td>
<td>2%</td>
<td>10%</td>
</tr>
<tr>
<td>6 Quadratic equity expense</td>
<td>$\zeta$</td>
<td>0.1%</td>
<td>0.1%</td>
</tr>
<tr>
<td>7 Discount rate (annual)</td>
<td>$\delta$</td>
<td>97%</td>
<td>95.75%</td>
</tr>
<tr>
<td>8 Expected loan loss rate (nondisaster)</td>
<td>$\eta$</td>
<td>3.0%</td>
<td>3.0%</td>
</tr>
<tr>
<td>9 St. dev. of loan loss rate (nondisaster)</td>
<td>$\theta$</td>
<td>0.24%</td>
<td>0.24%</td>
</tr>
<tr>
<td>10 Minimum capital requirement</td>
<td>$\kappa$</td>
<td>14%</td>
<td>14%</td>
</tr>
<tr>
<td>11 Disaster loan loss rate</td>
<td>$\psi$</td>
<td>3.5%</td>
<td>3.5%</td>
</tr>
<tr>
<td>12 Disaster probability (annual)</td>
<td>$P[s_{t+1} \geq 24.5^\circ]$</td>
<td>4.6%</td>
<td>4.6%</td>
</tr>
<tr>
<td>13 Insurance premium (loaded price)</td>
<td>$p$</td>
<td>8.05%</td>
<td>8.05%</td>
</tr>
<tr>
<td>14 Supervisory stringency</td>
<td>$\nu$</td>
<td>5</td>
<td>5</td>
</tr>
</tbody>
</table>

Note: New values reflect the lending rates and operational costs of a large bank in Peru; the original values are those from the studied lender used in Section 4.

Figure 11 illustrates the results. The results using this alternative calibration are qualitatively similar to those of the main text: insuring increases the \textit{ex ante} credit supply and reduces \textit{ex post} credit contraction, the uninsured FI manages its disaster risk using a capital buffer above regulatory requirements, the optimal sum insured with the loaded insurance is about half that for the actuarially fair insurance, etc. Some of the quantitative estimates differ. For example, the results here suggest that the actuarially fair insurance (loaded insurance) would expand \textit{ex ante} access to credit by about 10\% (8\%) versus 8\% (5\%) for the studied lender. Also, the uninsured studied lender recovers more quickly, returning to about 95\% of pre-event lending after 10 quarters versus 90\% for the larger lender. These differences emerge from the lenders’ profit margins: the higher lending interest rate of the smaller lender helps it recover more quickly through retained earnings. The smaller margins of the larger lender make the insurance more useful for expanding the \textit{ex ante} credit supply. The main finding from this section is that the qualitative results are consistent across specifications.
Panel A: Optimal Policy

Panel B: Disaster Simulation

Figure 11: Optimal policy and disaster simulation, alternative specification

Note: Figures include three cases: the lender 1) retains its risk, 2) insure at the actuarially fair rate, and 3) insures at the actuarially unfair, loaded rate observed in the El Niño insurance market. Panel A shows the optimal insuring and lending policies and the resulting expected capital ratio. Panel B provides an illustrative disaster simulation. The vertical axes are scaled to the mean value of the non-disaster steady state distribution for the lender that retains its risk. Calibration follows the “New Value” column of Table 4.