Loan Portfolio Performance and El Niño, an Intervention Analysis

Benjamin Collier, Ani L. Katchova, and Jerry R. Skees[1]

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[1] Benjamin Collier is a doctoral applicant, Ani Katchova is an assistant professor, and Jerry Skees is the H.B. Price Professor of Policy and Risk in the Department of Agricultural Economics at the University of Kentucky.

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Abstract

Purpose – This paper illustrates that natural disasters can significantly threaten financial institutions serving the poor. The authors test the case of a microfinance institution (MFI) in Northern Peru, where severe El Niño events create catastrophic flooding.

Design/methodology/approach – Portfolio-level, monthly data from January 1994 to October 2008 were examined using an intervention analysis. The paper tested whether the 1997-1998 El Niño increased problem loans and estimated the magnitude of the effect.

Findings – The results indicate El Niño significantly increased problem loans, specifically the level of restructured loans. While restructured loans averaged 0.5 percent of the total loan portfolio before the El Niño, the estimated cumulative effect of El Niño indicates that an additional 3.6 percent of the portfolio value was restructured due to this event.

Research limitations/implications – Future research could build on these results by modeling insurance-type mechanisms for the MFI. Additional research that replicates these analyses in another context would be highly valuable for comparison across natural disasters and financial institutions.

Practical implications – The findings demonstrate that the correlated risk exposure of many small borrowers can significantly affect the lender and the importance of considering bank management in assessing disaster risk of a financial institution.

Social implications – Lender strategies to minimize losses may require long-term restructuring that perpetuates the effects of the disaster in the community.

Originality/value – This paper may be of particular value to researchers and practitioners hoping to improve the effectiveness and efficiency of MFIs concentrated in regions exposed to natural disaster risk.

Keywords: Financial institutions, Natural disasters, Portfolio investment, Peru

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Natural disasters can significantly threaten financial institutions serving the poor. Moreover, without proper assessment of natural disaster risk, microfinance institutions (MFIs) experience the risk of either underestimating their exposure (threatening long-term stability) or overestimating their exposure (unnecessarily limiting access to credit). Thus, methodologies to enhance assessment of natural disaster risk for MFIs are needed. This study estimates the effects of a natural disaster on the lending portfolio performance of a financial institution serving the poor. Specifically, we have identified an MFI in Piura, a region in northern Peru severely affected by El Niño. Extreme El Niño events like those in 1982-83 and 1997-98 create catastrophic flooding that destroys transportation infrastructure, productive assets, crops, and private homes and disrupts the livelihoods of households engaged in a wide range of activities.

Background: Banking and Natural Disaster Risk

Access to financial services, especially credit, has played an increasingly important role in development economics theory and applications in the past four decades. Many households have gained access to microcredit and increasingly sophisticated approaches are being adopted to enhance the performance of financial institutions serving the poor. For example in some regions, banking regulators are governing financial institutions providing microfinance (http://www.sbs.gob.pe/portalSBS/), and credit rating agencies (e.g., Planet Rating and MicroRate) have emerged that specialize in MFIs. Such advancements are generally intended to enhance the efficiency, effectiveness, and stability of microfinance providers with the end result of increasing access to financial services at better terms (e.g., lower interest rates for loans). Yet, in this context, many challenges remain to providing microcredit to the poor. One such challenge is natural disaster risk.

Natural disasters result in spatially correlated losses that can substantially affect the lending portfolio, especially if the portfolio is geographically concentrated (Bessis, 1998; Skees and Barnett, 2006). In this context, correlated risks cannot be completely managed by increasing the number of borrowers if all borrowers have some exposure. Figure 1 presents a stylized version of this problem. In this example, the bank lends to *n* identical borrowers that are exposed to both idiosyncratic risk (e.g., death of the breadwinner, health problems in the household, etc.) and correlated risk (e.g., severe weather risk, price risk, etc.). As *n* increases, the concentration of the portfolio declines and the bank is less exposed to the idiosyncratic risks of borrowers; however, as the figure shows, the correlated risk exposure of the bank remains (see also Katchova and Barry, 2005, Garside *et al.,* 1999).

Natural disasters are categorized as a component of operational risk by banking regulators. There has been increasing recognition that 1) assessing and measuring operational risk is an important aspect of protecting bank solvency; and 2) the risks facing financial institutions (credit risk, market risk, operational risk, etc.) are interrelated (Basel Committee on Banking Supervision, 2004; Greuning and Bratanovic, 2009). To manage correlated risks, banking regulators require that lenders maintain certain levels of capital. Still, lenders may be uncertain of their level of exposure to a natural disaster, as assessing this risk can be quite difficult (Charnobai and Rachev, 2006; Garside *et al.,* 1999). Holding too little capital threatens the solvency of the lender when a catastrophe occurs. However, because banks typically operate on small profit margins but are highly leveraged (low capital-to-asset ratios), holding larger-than-necessary capital reserves can represent significant opportunity costs for lenders (Greuning and Bratanovic, 2009).

Intervention Analysis

A common methodology used to examine the effects of catastrophic events on business operations is intervention analysis. These analyses use time-series data and identify the occurrence of the event with dummy variables. The immediate and long-term effects of the event can then be modeled using the specification of the time-series model. Intervention analysis has been used to estimate the effects of a variety of disasters including the effects of the September 11 terrorist attacks on the airline industry (Guzhva, 2008); the 1986 nuclear disaster in Chernobyl on tourism in Sweden (Hultkrantz and Olsson, 1997); Hurricane Hugo on the business of a public hospital (Fox, 1996) and lumber prices (Prestemon and Holmes, 2000) in South Carolina; and floods, cyclones, earthquakes, and other disasters on daily values for an Australian capital market index (Worthington and Valadkhani, 2004).

In the context of financial institutions, intervention analysis has primarily been used to assess the effects of policy and regulation changes or how well capital markets integrate information. For example, Ortiz (1983) examines the effects of the devaluation of the Mexican peso on the ratio of U.S. dollars to pesos held as savings deposits in Mexican banks; Allen and Wilhelm (1988) analyze the effects of the 1980 Depository Institutions Deregulatory and Monetary Control Act on the market values of deposit-taking institutions; and Philippatos and Viswanathan (1991) examine the effects of the 1987 Brazilian debt moratorium announcement on the market value of U.S. banks. Much of the research on financial institutions has concentrated on the effects of an event on stock prices for publicly traded firms.

A wealth of literature exists regarding the effect of a specific event on the value of a financial institution in the event studies literature (MacKinlay, 1997). In some contexts, intervention analysis and event study methodologies are quite similar; however, generally intervention analysis examines a specific event while event studies often attempt to estimate the effects of a type of event. As a result, event studies more typically examine several event occurrences and rely on a contemporaneous baseline (e.g., the S&P 500 if the study is examining movements in stock prices) as a control parameter (Binder, 1998). El Niño, the event of interest in this study, has such significant effects on the banking industry throughout Peru limiting the ability to find a suitable contemporaneous control group. Additionally, this study examines the effect of a single extreme El Niño on one financial institution. Therefore, an intervention analyses methodology was chosen.

In sum, while intervention analysis and similar methodologies have been used to estimate the effects of catastrophic events on business performance, and these methodologies have been used to estimate the effects of a variety of events on bank performance, we are unaware of any published study estimating the effects of a catastrophic event on lender portfolio performance, especially for a financial institution serving the poor.

The purpose of this paper is to assess exposure of an MFI in Piura to the consequences associated with the extreme El Niño of 1997-98. Given a long time series, the effects of El Niño on the proportions of troubled loans in the lending portfolio (loans that are restructured from their original terms and loans that are late in payments) can be isolated and inferences can be developed regarding the effects of extreme natural disasters like those created by El Niño. The paper has two objectives. The first objective is to test a hypothesis that the 1997-98 El Niño significantly increased the levels of late and/or restructured loans in the lending portfolio. A significant increase would consist of a pattern of (one-tailed) statistically significant increases in late and/or restructured loans in the months leading up to, during, and after the 1997-98 El Niño. The pattern of results for late and restructured loans will be analyzed for additional insights into when El Niño began affecting the lending portfolio and what combination of late and restructured loans the MFI used to address these problems. The second objective is to estimate the magnitude of the effect on troubled loans. We anticipate that these analyses will highlight the significant operational risk associated with such a natural disaster to geographically concentrated financial institutions.

Piura

Piura is a diverse geographic region in northwestern Peru with a population of 1.7 million (Instituto Nacional de Estadística e Informática, 2007). Agriculture is an important livelihood in the region, employing 37 percent of the workforce, which almost exclusively works on small farms of less than 10 hectares (Instituto Nacional de Estadística e Informática, 2007; Oft, 2009; Trivelli, 2006). Along the Pacific coast, Piura is an arid region with good soils and irrigated agriculture, making it one of the most productive agricultural regions in Peru. Moving from the coast eastward, the region is dominated by trees crops such as coffee and cocoa as the terrain changes quickly to semi-tropical small mountains. Beyond these regions are the high Andes where agriculture supports local consumption. Fifty-four percent of the population in Piura is at or below the poverty line (Instituto Nacional de Estadística e Informática, 2007). Credit is an important component of livelihood enhancement for households in Piura, and organizations providing small-enterprise loans have grown significantly in recent years. For example, the loan portfolio of Caja Piura, one of the largest municipal banks in Piura and the lender whose portfolio is analyzed in this study, grew from USD 2.6 million in January 1994 to USD 312 million in October 2008 (http://www.sbs.gob.pe/portalSBS/). Caja Piura lends to a variety of commercial and retail clients with an emphasis in small-enterprise loans; its average loan size is USD 3,182 (Trivelli, 2006).

Piura is severely affected by El Niño (United States Agency for International

Development, 2006). El Niño events occur when ocean currents and trade winds deviate from their normal cycle in the Southern Pacific, resulting in elevated sea surface temperatures and warmer trade winds off the coast of Peru (McPhaden, 2003; Oldenborgh *et al.,* 2005). These warm trade winds meet cool air descending from the Andes Mountains causing excess rainfall from December through April in Piura. Signs of an impending El Niño occur several months before extreme rainfall begins (McPhaden, 2003). During extreme El Niño events such as those in 1982-83 and 1997-98, catastrophic flooding occurred, beginning early in the year, about February 1983 and February 1998. In these years, rainfall was 40 times above normal for January to April, and volume in the Piura River was 41 times above its median volume. Experts predict such an extreme El Niño may now occur as frequently as 1 in every 15 years (Skees and Murphy, 2009).

Orlove *et al.* (2004) report rumors of an impending El Niño event as early as March of 1997, and the Peruvian government announced the potential for an El Niño event in June 1997. Signals become stronger as the period of excess rainfall approaches, and forecasting transitions from whether or not an El Nino event will occur to predicting the magnitude of the event. Ex post surveys conducted by Orlove *et al.* (2004) indicated that many households in Peru were unable to identify the specific month when they first heard the forecast of an impending El Niño, but roughly 60 percent of the survey reported having heard by June 1997. Orlove *et al.*, (2004) also found many households engaged in risk mitigating activities such as securing their homes before extreme rainfall and flooding began. They note that, especially for those in vulnerable economic sectors such as fishing, households were making these investments when entering a time of expected reduced income due to the impending natural disaster. These conditions put additional pressure on household budgets and would increase the opportunity cost of repaying loans. Thus, it may be the case that competition for household funds reduced repayment rates even in the months leading up to the catastrophic flooding.

The consequential losses associated with the 1997-98 El Niño were quite severe. Agricultural production declined by 30 percent (Cruzado Silveri, 1999; Skees and Murphy, 2009). Extreme flooding damaged or destroyed roads, bridges, reservoirs, irrigation systems, and other public infrastructure, which disrupted trade and created additional losses for enterprises in Piura. These disruptions resulted in cash flow problems and consequently affected the financial institutions supporting local enterprises (Oft, 2009).

Beyond the immediate effects of a catastrophe such as El Niño, the *risk* of a natural disaster constrains social and economic development in many regions. It seriously affects access to and terms of credit, and access to other input markets for agriculture and other small enterprises. Farmers facing high risk exposure and limited access to markets choose low-risk and low-return strategies (e.g., slower rates of technological adoption). Skees and Barnett (2006) provide the motivation for understanding how important default risks are to the operation of financial institutions in the context of natural disasters and use Piura as an example. By using a standard equation to account for default risk in interest rates (e.g., see Armendáriz and Morduch, 2010) and a Markov process for a 1 in 15 year event with a spike of around 10 percentage points in problem loans due to El Niño, interest rates in the region could be around 300 basis points higher due only to risks tied to El Niño. Additionally, Boucher *et al.* (2008) conclude that alleviating such credit constraints in Piura would raise output value by 26 percent. Thus, understanding more about how El Niño risk affects the financial sector is extremely important for improving both access to and terms of credit for small holders as well as contributing to larger economic development goals for the region.

Model and Data

The data used in these analyses are monthly, bank-level data from January 1994 to October 2008 (resulting in 178 time-series observations) for a municipal bank in Piura, Caja Piura. The data for these analyses come from the website of the banking regulator in Peru, Superintendencia de Banca, Seguros y AFP (called SBS hereafter). SBS posts key balance sheet variables for each bank.[2] The SBS data divide the loan portfolio into three categories: valid, late, and restructured loans. Valid loans are those that are being repaid based on the initial loan terms. Late loans indicate the total balance of loans that are overdue. Loans are moved from the valid to the late category depending on the type of loan. For example for commercial loans, the loan becomes overdue if payment is more than 15 days late and for micro-loans, if payment is more than 30 days late. The late loans category also includes the value of loans in judicial collection. Restructured loans are those for which the maturity dates and/or the original loan amounts have been changed, typically due to repayment difficulties of the borrowers. Poorly performing loans tend to move from the valid loan category to the late loan category and then to the restructured category (http://www.sbs.gob.pe/portalSBS/).

The first dependent variable in these analyses is the proportion of loans in the restructured category (shown in Figure 2), which is calculated by dividing the value of restructured loans by the total value of all loans in the portfolio. Restructured loans represent losses in outstanding principal and increased costs including the added administrative costs associated with restructuring the loan. Typically, banks restructure loans when borrowers experience extenuating circumstances that affect their ability to repay. Banks choose to restructure loans because it tends to reduce the overall losses they experience (compared to not restructuring) by allowing the borrower to repay under new terms. Such concessions represent

[2] The website of SBS: http://www.sbs.gob.pe/portalSBS/ provides the data and description of the variables.

current losses in bank assets, but also opportunity costs associated with holding poorly performing loans for months or even years. Thus, spikes in the proportion of restructured loans are likely to have longer-term costs for the bank. The banking regulator uses the proportion of restructured loans as an indicator of the asset quality of the bank.

The second dependent variable in these analyses is the proportion of loans in the late category (shown in Figure 3), which is calculated by dividing the value of late loans by the total value of all the loans in the portfolio. It is worth noting that while banks cannot directly control whether borrowers are repaying their loans or not, they can choose what proportion of their loans to restructure and thus have some control of the overall level of late loans in the portfolio. To a bank, late loans represent losses in monthly bank revenue, increased provisioning requirements, and reduced likelihood of repayment. Late loans are also an important indicator of asset quality.

The independent variables included in the model are dummy variables to identify the months before, during, and after the El Niño event. [3] Catastrophic flooding began in February of 1998; however, as described in the literature review, forecasting signals of an impending El Niño developed several months before the event. Because El Niño forecasting occurs several months before the event and increases in accuracy as the impending event approaches, we anticipate that these forecasts may affect the performance of late and restructured loans. If so, a pattern of significantly increased late loans in the months leading up to El Niño should occur. To test for this possibility regarding late loans, we include monthly dummies as early as June 1997, when the government forecasted a potential El Niño event. We include dummies through September of

[3] While using dummy variables as the means to identify the event is a common practice in intervention analysis, it is worth noting the limitations of this approach. A dummy variable in a time series model captures the model residual for that period. Thus, the dummy variable can correctly be considered the deviation from the conditions specified by the model parameters. In cases where the event is quite salient, such as El Niño in northern Peru, it may be reasonable to assume that the model residual is largely explained by the event; however, the accuracy of the dummy variable estimation depends in part on how well the model is specified.

1998 to account for the possibility that deteriorating loan performance may not occur immediately after the flooding for loans that mature at the end of a production period.

Because banks experience losses and costs from restructuring loans, we anticipate that if they use forecasting information in their decision to restructure loans, it will occur later in the year when forecasting information is stronger. The severity of the El Niño may affect how significantly they alter the terms of the loan during the restructuring process. We include monthly dummies from October 1997 through September 1998 for the analyses of restructured loans,

Examining late and restructured loans concurrently enhances the interpretation of an effect in either category and provides insights into the management strategies of the bank. For example, the data may suggest a pattern in which late loans increase during the event then, several months after the event, the proportion of restructured loans increases. If this pattern occurred it would likely be an indication that some borrowers had difficulty making loan payments during El Niño, and that the bank restructured loans for troubled borrowers based on their reduced repayment capacity due to the event. Alternatively, finding an El Niño effect on the proportion of late loans but not on restructured loans would likely be an indication that the bank is taking a passive approach to managing troubled assets in the lending portfolio associated with El Niño.

Estimation Procedures

The model involves a two step procedure: time series estimation and intervention analysis. Completing our first objective — testing whether the 1997-98 El Niño significantly increased the levels of late and/or restructured loans in the lending portfolio — requires fitting a time series model and testing the monthly dummies for significance. If the effect of El Nino on late and/or restructured loans is significant, completing our second objective — estimating the magnitude of the effect — requires applying intervention analysis to the results from the time series model.

Fitting the Time-Series Model

We use a Box-Jenkins methodology to fit the time-series model (Box and Jenkins, 1968, see also Enders, 2004; Greene, 2000; Pindyck and Rubinfeld, 1997). First, we test the stationarity of the dependent variable (first for proportion of restructured loans then for proportion of late loans). Stationarity indicates that characteristics of the dependent variable (e.g., mean and variance) are not changing across the time-series, and therefore can be estimated with fixed coefficients for each independent variable. If restructured loans or late loans is not stationary, several approaches can be used to transform the data, the most common of which is taking the first difference of the dependent variable ($\Delta y_t = y_t - y_{t-1}$). Second, we analyze the data to select the appropriate time-series model. The intention of the time-series procedures is to create an independent and identically-distributed process by accounting for autoregressive (AR) and/or moving average (MA) relationships in the model (see Greene, 2000; Enders, 2004). AR processes are a relationship between current and previous values of the dependent variable; MA processes are a relationship between current values of the dependent variable and previous values of the error term. Thus, the basic time-series model can be written

$$y_t = \mu + \sum_{p=1}^{P} \gamma_p y_{t-p} + \epsilon_t + \sum_{q=1}^{Q} \theta_q \epsilon_{t-q}$$

where y_t is the dependent variable, μ is the intercept term, ϵ_t is the error term, p denotes the AR term, q denotes the MA term, γ_p is the coefficient for the corresponding AR term, and the θ_q is the coefficient for the corresponding MA term. Time-series models that both correct for stationarity using differencing and incorporate AR and/or MA terms are referred to as autoregressive integrated moving average (ARIMA) models. We examine the model residuals using the autocorrelation (ACF) and partial autocorrelation functions (PACF) to estimate the dependence order (the AR and MA processes) of the model. The ACF and PACF describe correlations between the dependent variable in the current period and model residuals from previous periods (see Greene, 2000, or Enders, 2004). Diagnostic tests are also used to identify the best-fitting model. We use goodness of fit tests including the Akaike Information Criterion (AIC) and Schwarz Bayesian Information Criterion (SBC), the Ljung-Box Q statistic for white noise, and the coefficients of the lag variables to assess the models (see Enders, 2004). We then test the time series model for stability — that is that the autoregressive structure of the model will not cause it to diverge over time. A necessary condition for stability is $\sum_{i=1}^{p} \gamma_i < 1$, a sufficient condition for stability is $\sum_{i=1}^{p} |\gamma_i| < 1$ (Enders, 2004).

After appropriately fitting the time series model, we use maximum likelihood estimation to test the coefficients on the monthly dummies to determine if El Niño significantly increases the proportion of late and/or restructured loans in the lending portfolio. Additionally, the model can be used to identify the pattern and timing in which troubled loans developed by comparing the effects on late loans to those on restructured loans. If El Niño has no significant effect, no additional analyses are needed.

Intervention Analysis

Regarding the second objective, the time series must be altered to improve estimation of the magnitude of the event. First, we identify and control for extreme values of the dependent variable that are not associated with the El Niño event of interest — outliers. While controlling for such outliers should improve the fit of the model, the intervention analysis literature warns of over-fitting by including too many outliers (e.g., Greene, 2000); therefore, we include up to four outliers with an inclusion criteria that their values must deviate from the mean with significance level of $\alpha < 0.01$ (two-tailed test). Finally, we re-estimate the time-series model with the outlier dummies included.[4]

It should be noted that excluding outliers when testing a null hypothesis truncates the distribution and biases the results, increasing the likelihood of a significant result. Thus, for our first objective — a hypothesis test that El Niño significantly increases troubled loans — we estimate a time series model without outlier dummies. In contrast, when an outlier is clearly not associated with the event of interest (e.g., in our data if an outlier occurs several years before the 1997-98 El Niño event) including it in the model reduces the precision of the estimate of that event. Not only do these outliers increase the variance unaccounted for in the model, but they can affect the estimation of the coefficients and the lag structure of the model. Therefore, for our second objective — estimating the magnitude of the effect of El Niño on the lending portfolio — we include outlier dummies to reduce unrelated variance.

The intervention analysis employs the time-series model controlling for outliers by including dummy variables for the outliers to estimate the effects of the event. We use a maximum likelihood estimation to assess the effects of the El Niño dummies on the restructured loans and/or late loans. The magnitudes of the coefficients for the event dummies represent the immediate effects of the 1997-98 El Niño (Enders, 2004). For example, consider a model with a one period AR lag

$$y_t = \mu + \gamma_1 y_{t-1} + bS + cD + \epsilon_t$$

Where S is an outlier dummy and D is an event dummy. The immediate effect of the event is the

[4] Consistent with the previous footnote describing the limitations of dummy variables, identifying outliers with dummy variables can have important model implications. An outlier may be an indication of an extreme event unrelated to the event of interest or of an extreme value of an important explanatory variable excluded from the model. When researchers are unable to identify the cause of outlying values, a cautious approach is best as including a large number of outlier dummies may result in over-fitting the model to available observations (see Greene, 2000).

coefficient of the dummy variable c. We only analyze the effects for the event dummies that have an immediate effect, that is significant at least at the one-tailed α=0.05 level, in the original time series model, the model *before* the outliers are omitted.

We also estimate the long-term effects of the event based on the structure of the time-series model, specifically, the AR process (Enders, 2004). The AR process indicates how current values of the dependent variable relate to future values. For example using the one period AR lag model above, the effect of the dummy variable on the independent variable in the current period y_t affects the value of the independent variable in the next period y_{t+1} because of the AR structure

$$y_{t+1} = \mu + \gamma_1 y_t + bS + cD + \epsilon_{t+1}$$

by substitution for y_t

$$y_{t+1} = \mu + \gamma_1(\mu + \gamma_1 y_{t-1} + bS + cD + \epsilon_t) + bS + cD + \epsilon_{t+1}$$

Thus, when shocks associated with the event enter the model, their total effects must be estimated using the AR terms specified in the time-series model. For example, for the model with one AR lag

$$\frac{dy}{dD} = c\left[1 + \gamma_1 + \gamma_1^2 + \cdots + \gamma_1^j\right] = \sum_{k=0}^{j} c\gamma_1^k$$

where y is the dependent variable, D is the event dummy, c is the coefficient on the event dummy, γ_1 is the coefficient on the AR variable, and j represent future periods in the time-series $(t, t+1, t+2, \ldots, t+j)$.

Results

In this section, the time-series and intervention analysis procedures described in the previous section are applied to estimate the effects of the 1997-98 El Niño on the proportion of restructured loans and on the proportion of late loans in the lending portfolio of Caja Piura. The results are organized around the objectives identified in the introduction — first, we test for a significant increase in problem loans due to El Niño, then if significant, we estimate the magnitude of the effect.

The augmented Dickey-Fuller test was used to assess the stationarity of the proportion of restructured loans (y_t) and the proportion of late loans (l_t). This test indicates that the proportion of restructured loans and the proportion of late loans are both nonstationary; however, the differenced proportion of restructured loans and the differenced proportion of late loans are stationary, shown in Table 1. Therefore, we use the differenced proportion of restructured loans, or change in the proportion of restructured loans (i.e., $\Delta y_t = y_t - y_{t-1}$; shown in Figure 4) and the change in proportion of late loans (Δl_t) as the dependent variables in the following analyses.

Testing for a Significant Increase in Restructured Loans and/or Late Loans

For restructured loans, inspection of the ACF and PACF and the model fit statistics indicate an AR lag structure with a lag at the third (Δy_{t-3}) and seventh (Δy_{t-7}) periods and no MA terms. The necessary and sufficient conditions for stability hold for this time-series model. The maximum likelihood estimation suggests significant effects of the El Niño event on the change in proportion of restructured loans in December 1997, January, March, April and May 1998, reported in Table 2. Significant effects in December and January indicate loans were being restructured *before* the catastrophic flooding due to El Niño began in February 1998. Significant effects in March, April, and May 1998 coincide with the major period of flooding due to El Niño. By June 1998, the proportion of restructured loans seems to have reached a plateau as no significant increases in the proportion of restructured loans are found in the monthly dummies after June.

For late loans, the time-series estimation indicates a good fit for a model with an AR lag at the seventh period (Δl_{t-7}). The necessary and sufficient stability conditions hold for this model. Results for the maximum likelihood estimation for the change in the proportion of late loans indicate that late loans *were not affected* during the 1997-98 El Niño, reported in Table 3. The results show a significant increase in late loans in August 1997; however, this result does not fit the hypothesized pattern of a several-month increase in late loans leading up to or during the El Niño event.

Testing indicates El Niño had no significant effect on late loans; therefore, no additional statistical analyses are conducted with late loans. Since El Niño significantly increased the proportion of restructured loans, we continue the estimation process to assess the magnitude of the effect.

Discussion of Objective 1: Hypothesis Testing

The results of a significant effect on the performance of restructured loans but no consistent effect on the performance of late loans is likely an indication that the MFI actively restructured loans as problems emerged. While a significant increase in late loans occurred in August 1997, this finding seems inconsistent with the hypothesis that borrowers were failing to repay their loans in order to make risk mitigating investments as there is not a consistent increase in late loans in the months leading up to El Niño.

Instead, the results support the image of a lender that is actively managing its loan portfolio. Results suggest that Caja Piura even used El Niño forecasting signals to restructure loans before the catastrophe occurred. In this fashion, the bank likely experienced losses associated with loan restructuring — both losses in principal and increased operational costs — before borrowers experienced losses. The surprising finding of no significant increase in the proportion of late loans before, during, or after the event also supports the conclusion that the bank had a strong preference for restructuring loans rather than increasing its portfolio of late loans and was working dynamically to minimize losses as problems emerged. The lender might be motivated to take this strategy due to higher provisioning rates for late loans than restructured loans or as a means to encourage borrowers to continue paying rather than defaulting as their capacity to pay changed.

Estimating the Magnitude of the Effect

To improve estimation of the magnitude of the effect, the four most significant outliers — May 1994, December 1994, December 2002, and March 2008 — are added as dummy variables to the model to improve fit Excluding values associated with the 1997-98 El Niño, these outliers represent the most extreme changes from one period to the next. We do not know the specific events that occurred during these months to cause such significant changes in the proportion of restructured loans.

The time-series process was again tested and several autoregressive structures were compared. The analyses indicated no MA terms should be included, but that two AR models — one AR model for periods $p = 1, 2, 3,$ and 7 and one AR model for periods $p = 1, 2,$ and 3 — are suitable according to ACF and PACF residuals and the goodness of fit and white noise measures, shown in Table 4. Because these models are comparable, the AR model with lags at 1, 2, and 3 is chosen for parsimony. Thus, the model is

$$\Delta y_t = \mu + \gamma_1 \Delta y_{t-1} + \gamma_2 \Delta y_{t-2} + \gamma_3 \Delta y_{t-3} + bS + cD + \epsilon_t$$

The necessary and sufficient conditions for stability hold for this model.

Second, we apply the intervention analysis procedure. Given this model, we use a maximum likelihood estimation to examine the immediate effects of El Niño on the change in the proportion of restructured loans, results shown in Table 5. The immediate effect is seen in the monthly dummy variables for those months with significant increases for the time series model used in hypothesis testing — December 1997, January, March, April, and May 1998.. The largest immediate effect is seen in March 1998 when the proportion of restructured loans increases by 0.86 percent of the value of the loan portfolio.

To estimate the long-term effects, we return to the dependence order of the model. The process for estimating long-term effects for a model with a single AR term is described in the Model and Data section. Extending the example from that section to the time-series model in this analysis, which has three AR terms, leads to the following

$$\frac{d\Delta y}{dD_m} = c\left[1 + \gamma_1 + \gamma_1^2 + \cdots + \gamma_1^j + \gamma_2 + \gamma_2^2 + \cdots + \gamma_2^{j-1} + \gamma_3 + \gamma_3^2 + \cdots + \gamma_3^{j-2}\right]$$

where D_m represents the dummy for each of the months (e.g., March 1998) and the *j*th superscript represents the final value of k included for which $c\gamma_i^k$ is arbitrarily close to zero — this term converges to zero at an exponential rate as k increases. The term converges to zero after roughly 10 periods for this El Niño event based on the coefficients in the model. To identify the entire effect of El Niño on the change in proportion of restructured loans, the long-term effects for all significant months must be added together, shown in Table 6.[5] These analyses indicate El Niño had a total cumulative effect of 3.8 percent, that is, the proportion of restructured loans increased by 3.8 percent of the value of the total loan portfolio due to the 1997-98 El Niño.

Discussion of Objective 2: Estimating the Effect of El Niño

The total estimated increase in the proportion of restructured loans at a level of 3.8 percent of the

[5] Confidence intervals are also included in Table 5 to assist the reader in evaluating the precision with which the immediate effects are evaluated.

total portfolio represents the highest magnitude effect of the 1997-98 El Niño event when examining the loan portfolio. That is, the lender would have experienced a permanent 660 percent increase in restructured loans if the loans never matured and the bank took no further action to minimize losses.[6] The actual proportion of restructured loans fails to reach this magnitude most likely because of actions taken by the lender to stem losses. As can be seen in Figure 2, the proportion of restructured loans declined following the event, perhaps due to debt-forgiveness policies of the bank, but for several years, the bank maintained a higher proportion of restructured loans than before the event.

Conclusions and Policy Implications

This study uses time-series estimation and intervention analysis to test and estimate the effects of the 1997-98 El Niño on loan portfolio performance for a rural lender in Peru. The event significantly increased the proportion of restructured loans but did not increase the proportion of late loans in the portfolio. The total effect of El Niño was estimated as an increase in restructured loans of 3.8 percent of the total value of the loan portfolio. The largest single immediate effect for restructured loans occurred in March 1998 when the increase was equivalent to 0.86 percent of the lending portfolio.

The immediate and total effects of the 1997-98 El Niño event are dramatic. The average proportion of restructured loans from January 1994 to November 1997 was 0.5 percent, indicating the event increased the proportion of restructured loans 660 percent above the average value. Given that the value of the total loan portfolio before the event in November 1997 was 54.6 million Peruvian Nuevo Soles (PEN), the estimated total value of loans restructured due to

[6] Using the differenced data, which is required for this time-series to be stationary, necessitates conceptualizing the change due to the El Niño event as permanent. The analyses do not provide any indication as to how quickly the lender can recover from the event. Evaluating lender recovery requires information about bank policies (average loan maturity for restructured loans, the extent to which loans were forgiven, etc.), bank liabilities (e.g., savings deposits), and systemic events such as political interventions, which is beyond the scope of this paper.

the 1997-98 El Niño was PEN 2.1 million, roughly USD 771,000 (in 1997 dollars).[7]

These analyses demonstrate three primary themes regarding loan portfolio performance and natural disaster risk. First, the correlated risk exposure of many small borrowers can lead to large effects in the lending portfolio when a catastrophic event occurs. This finding is not new and is consistent with the emphasis of the Basel Committee on the interrelatedness of operational and credit risks; however, this case is a dramatic example of this exposure. These findings are worthy of careful consideration by regulators managing MFIs as they may challenge the sufficiency of generally accepted operational risk assessment approaches in some contexts. For example in Peru, Caja Piura and similar MFIs are regulated under standards quite similar to Basel II (see Superintendencia de Banca, Seguros y AFP, 2009). Under these regulations MFIs hold capital to manage their operational risk based on a percentage of their annual positive gross income from the previous three years.[8] Estimating operational risk based on gross income levels may be insufficient for banks concentrated in regions exposed to significant natural disaster risk. We recognize many MFIs are not under ongoing regulatory supervision, and for these institutions prudent consideration on the part of owners and managers is needed.

In practice, such catastrophic events have led some microcredit providers to ration credit, especially for agriculture which can be one of the economic sectors most highly exposed to the correlated risks that are tied to natural disasters. Caja Piura began rationing credit to agriculture after the 1997-98 El Niño (Tarazona and Trivelli, 2006). While limiting exposure to correlated risk through credit rationing is an understandable approach for lenders, it can both impede growth for the bank and development in the region (Boucher *et al.,* 2008). It is also worth noting

[7] The exchange rate in the fall of 1997 was 2.66 PEN to 1 USD (United States Central Intelligence Agency, 2002).

[8] Two approaches under Basel II require basing capital requirements for operational risk on gross income: the Standardized Approach and the Basic Indicator Approach (BCBSm 2004). There a more advanced approach for managing operational risk, but as of January 2010, the Peruvian banking regulator reported no banks use the most advanced approach in Peru.

again the significant infrastructure and household income losses that had widespread effects in Piura extending beyond agriculture (Oft, 2009). Such reports of widespread losses challenge the effectiveness of agricultural credit rationing strategies for MFIs in this region, as well. More efficient and effective risk management mechanisms such as those that transfer these risks through insurance or securitization have the potential to greatly improve the performance of microcredit providers.

Second, the findings emphasize the importance of considering bank management in assessing disaster risk to a loan portfolio. A theme from the diverse intervention analysis and event studies literatures is that the effects of natural disasters are often context-specific. Likewise, many factors determine the way banks optimize portfolio performance that are based on the risk, local institutions, culture, and available disaster relief mechanisms. Perhaps the most fascinating aspect of the analyses in this study is the evidence that Caja Piura likely used forecasting information to restructure loans before significant losses occurred.

Third, the findings imply that bank strategies to minimize losses may require long-term restructuring that perpetuates the effects of the disaster in the community. These analyses show that Caja Piura restructured nearly all the loans affected by El Niño, and reports from the region indicate that the terms of restructuring included extending the loan years into the future (Tarazona and Trivelli, 2006). Not only do such repayment plans create long-term indebtedness among local borrowers, but they tie up bank capital that could otherwise be used to expand access to credit. Findings in other regions of the world indicate these long-term consequences to the community are common among other types of disasters, as well (Dercon, 1998; GlobalAgRisk, 2009). Thus, bank policies combined with risk transfer mechanisms, perhaps risk transfer mechanisms for borrowers, that offer credible alternatives to long-term loan restructuring have the potential to improve recovery time for the community or region. Careful consideration is needed to develop clear ex ante rules for these policies as ad hoc debt forgiveness can entrench borrower expectations of nonrepayment that contribute to longer term credit constraints.

Important follow-up analyses could advance this work. “Natural disasters” encompasses a broad category of events and El Niño probably poorly represents some types of disasters. For example, the effects of drought may not be as pervasive as flooding as it is not likely to destroying transportation infrastructure, homes, or buildings. Thus, these methods could be replicated for lenders that have experienced other disasters, which may lead to problem loans and the need for restructuring. Additionally, each occurrence of the same natural disaster can have significantly different effects (Jobst, 2007); therefore, comparing these findings to analyses using data for previous extreme El Niño events, such as the one in 1982-83, may be insightful.

References

Armendáriz, B. and Morduch, J. (2010), "Subsidy and sustainability", in *The Economics of Microfinance*, 2nd ed., MIT Press, Cambridge, MA, pp. 231-256.

Basel Committee on Banking Supervision (2004), *International Convergence of Capital Measurement and Capital Standards: A Revised Framework,* Bank for International Settlements, Basel, Switzerland.

Bessis, J. (1998), "Correlations and portfolio risk", in *Risk Management in Banking*, John Wiley & Sons, New York, NY, pp. 289-297.

Binder, J.J. (1998), "The event study methodology since 1969", *Review of Quantitative Finance and Accounting,* Vol. 11 No. 2, pp. 111-137.

Box, G.E.P. and Jenkins, G.M. (1968), "Some recent advances in forecasting and control", *Journal of the Royal Statistical Society. Series C (Applied Statistics),* Vol. 17 No. 2, pp. 91-109.

Boucher, S., Carter, M. and Guirkinger, C. (2008), "Risk rationing and wealth effects in credit markets: theory and implications for agricultural development", *American Journal of Agricultural Economics,* Vol. 90 No. 2, pp. 409-423.

Charnobai, A. and Rachev, S.T. (2006), "Applying robust methods to operational risk modeling", *Journal of Operational Risk,* Vol. 1 No. 1, pp. 27-41.

Cruzado Silveri, E. (1999), "El fenómeno El Niño en Piura 97/98 y el rol del estado: consecuencias sectoriales y sociales 7", report, Centro de Investigacion y Promocion del Campesinado (CIPCA), Departamento de Investigacion Socioeconomica, Piura, Peru.

Dercon, S. (1998), "Wealth, risk, and activity choice: cattle in western Tanzania", *Journal of Development Economics,* Vol. 55 No.1, pp. 1-42.

Enders, W. (2004), *Applied Econometric Time-Series*, 2nd ed., John Wiley & Sons, Hoboken, NJ.

Fox, R.T. (1996), "Using intervention analysis to assess catastrophic events on business environment", *International Advances in Economic Research,* Vol. 2 No. 3, pp. 341-349.

Garside, T., Stott, H. and Stevens, A. (1999),"Credit portfolio management", available at: http://www.erisk.com/learning/research/013_200creditportfoliomodels.pdf (accessed 23 April 2010).

GlobalAgRisk (2009), The Role of Risk Assessment in Setting Insurance Priorities and Policy, Vol. 2, *Developing Agricultural Insurance in Vietnam: Four Educational Handbooks*, AgroInfo, Hanoi, Vietnam.

Greene, W.H. (2000), *Econometric Analysis,* 4th ed., Prentice Hall, Upper Saddle River, NJ.

Greuning, H. and Bratanovic, S.B. (2009), *Analyzing Banking Risk: A Framework for Assessing Corporate Governance and Risk Management*, 3rd ed., The World Bank, Washington, DC.

Guzhva, V.S. (2008), "Applying intervention analysis to financial performance data: the case of US airlines and September 11th", *Journal of Economics and Finance,* Vol. 32 No. 3, pp. 243-259.

Hultkrantz, L. and Olsson, K. (1997), "Chernobyl effects on domestic and inbound tourism in Sweden—a time-series analysis", *Environmental and Resource Economics,* Vol. 9 No. 2, pp. 239-258.

Instituto Nacional de Estadística e Informática (2007), "Perú: perfil de la pobreza según departamentos, 2004–2006", report REF HC 230.P6 I51P, Instituto Nacional de Estadística e Informática, Lima, Peru, December.

Jobst, A. (2007), "Operational risk: the sting is still in the tail but the poison depends on the dose", working paper WP/07/239, International Monetary Fund, Washington, DC, November.

Katchova, A. and Barry, P. (2005), "Credit risk models and agricultural lending", *American Journal of Agricultural Economics*, Vol. 87 No. 1, pp. 194-205.

MacKinlay, A.C. (1997), "Event studies in economics and finance", *Journal of Economic Literature,* Vol. 35 No. 1, pp. 13-39.

McPhaden, M.J. (2003), "El Niño and La Niña: causes and global consequences", in MacCracken, M.C. and Perry, J.S. (Eds.), *Encyclopedia of Global Environmental Change, Volume 1, The Earth System: Physical and Chemical Dimensions of Global Environmental Change,* John Wiley & Sons, Hoboken, NJ, pp. 353-370.

Prestemon, J.P. and Holmes, T.P. (2000), "Timber price dynamics following a natural catastrophe", *American Journal of Agricultural Economics,* Vol. 82 No. 1, pp. 145-160.

Philippatos, G.C. and Viswanathan, K.G. (1991), "Brazilian debt crisis and financial markets: an analysis of major economic events leading to the Brazilian debt moratorium", *Applied Financial Economics*, Vol. 1 No. 4, pp. 223-234.

Pindyck, R.S. and Rubinfeld, D.L. (1997), *Econometric Models and Economic Forecasts,* 4th ed., McGraw-Hill, New York, NY.

Oft, P. (2009), “Can resilience be built through microfinance tools? A case study of coping and adaptation strategies to climate-related shocks in Piura, Peru”, PhD dissertation, University of Bonn, Germany, March.

Oldenborgh, G.J., Philip, S.Y. and Collins, M. (2005), “El Niño in a changing climate: a multi-model study”, *Ocean Science,* Vol. 1 No. 2, pp. 81-95.

Orlove, B.S., Broad, K. and Petty, A.M. (2004), “Factors that influence the use of climate forecasts: evidence from the 1997/98 El Niño event in Peru”, *American Meteorological Society,* Vol. 85 No. 11, pp. 1735-1743.

Superintendencia de Banca, Seguros y AFP (2009), “Resolución S.B.S. N°2115-2009, Reglamento para el requerimiento de patrimonio efectivo por riesgo operacional”, Superintendencia de Banca, Seguros y AFP, Lima, Perú, 2 April.

Superintendencia de Banca, Seguros y AFP (2008), “Resolution 11356-2008, Se aprueba el nuevo reglamento para la evaluación y clasificación del deudor y la exigencia de provisiones”, Superintendencia de Banca, Seguros y AFP, Lima, Perú, 19 November.

Skees, J.R. and Barnett, B.J. (2006), “Enhancing micro finance using index-based risk transfer products”, *Agricultural Finance Review,* Vol. 66 No. 2, pp. 235-250.

Skees, J.R. and Murhpy, A.G. (2009) “ENSO Business Interruption Index Insurance (EBIII) for catastrophic flooding in Piura, Peru”, working paper, GlobalAgRisk, Inc., Lexington, KY, 12 February.

Tarazona, A. and Trivelli, C. (2006), “Financiamento rural en Piura: informe final”, final report, Instituto de Estudios Peruanos, Lima, Peru, January.

Trivelli, C. (2006), “Rural finance and insurance on the north coast of Peru”, summary report 2005/06, Instituto de Estudios Peruanos, Lima, Peru, September.

United States Agency for International Development (2006), “Hedging weather risk for microfinance institutions in Peru: comprehensive report”, report prepared by GlobalAgRisk, Inc., United States Agency for International Development, Washington, DC, November.

United States Central Intelligence Agency (2002), “Field listing—Exchange rates, The World Factbook 2002”, available at: http://www.faqs.org/docs/factbook/fields/2076.html (accessed 23 April 2010).

Worthington, A. and Valadkhani, A. (2004), “Measuring the impact of natural disasters on capital markets: an empirical application using intervention analysis”, *Applied Economics,* Vol. 36 No. 19, pp. 2177-2186.

Table 1. Summary Statistics and the Augmented Dickey-Fuller Test for the Proportion of Restructured Loans and Late Loans

	Proportion of Restructured Loans y_t	Change in Proportion of Restructured Loans Δy_t	*Proportion of Late Loans* l_t	*Change in Proportion of Late Loans* Δl_t
Observations	178	177	178	177
Mean	0.0151	0.0001	0.0595	-0.0002
Standard deviation	0.0090	0.0027	0.0135	0.0051
Maximum	0.0351	0.0137	0.1142	0.0262
Minimum	0.0004	-0.0125	0.0262	-0.0237
ADF statistics	F	F	F	F
Constant Only	2.40	72.90***	4.57*	90.24***
	(0.460)[a]	(0.001)	(0.053)	(0.001)
Constant and Trend	2.45	72.64***	4.96	90.02***
	(0.688)	(0.001)	(0.185)	(0.001)

*** indicates significance at the p=0.01 level

[a] p values in parentheses

Table 2. Maximum Likelihood Estimation for Change in the Proportion of Restructured Loans Δy_t, One-Tailed Test

Parameter	**Estimate**	**Standard Error**
μ	-0.0001	0.0002
Δy_{t-3}	-0.1975	0.0751
Δy_{t-7}	0.2230***	0.0755
October 1997	0.0000	0.0025
November 1997	0.0014	0.0025
December 1997	0.0057***	0.0024
January 1998	0.0046**	0.0025
February 1998	0.0018	0.0025
March 1998	0.0089***	0.0024
April 1998	0.0052**	0.0024
May 1998	0.0044**	0.0025
June 1998	0.0006	0.0025
July 1998	-0.0015	0.0024
August 1998	-0.0049	0.0025
September 1998	-0.0015	0.0025
Number of Residuals	177	
Standard Error	0.002454	

Ljung-Box Q-statistic[a]	
Q(6)	8.59
	(0.072)
Q(12)	10.39
	(0.407)
Q(18)	11.18
	(0.798)

* Indicates significance at the p=0.10 level, one-tailed test; ** Indicates significance at the p=0.05 level, one-tailed test; *** Indicates significance at the p=0.01 level, one-tailed test

[a] p values in parentheses

Table 3. Maximum Likelihood Estimation for Changes in Proportion of Late Loans Δl_t

Parameter	**Estimate**	**Standard Error**
μ	-0.0003	0.0003
Δl_{t-7}	-0.2722	0.0768
June 1997	-0.0004	0.0050
July 1997	0.0040	0.0050
August 1997	0.0094*	0.0050
September 1997	0.0016	0.0050
October 1997	0.0062	0.0050
November 1997	-0.0015	0.0050
December 1997	-0.0161	0.0050
January 1998	0.0052	0.0051
February 1998	0.0040	0.0051
March 1998	0.0003	0.0050
April 1998	0.0042	0.0050
May 1998	-0.0064	0.0050
June 1998	0.0008	0.0050
July 1998	0.0006	0.0050
August 1998	0.0041	0.0050
September 1998	-0.0002	0.0050
Number of Residuals	177	
Standard Error	0.0050	

Ljung-Box Q-statistic[a]	
Q(6)	3.41
	(0.636)
Q(12)	5.59
	(0.899)
Q(18)	17.66
	(0.411)

* Indicates significance at the p=0.10 level, one-tailed test

[a] p values are in parentheses

Table 4. Comparison of ARIMA Models for Change in the Proportion of Restructured Loans Δy_t

AR structures	Model with AR lags p=1, 2, 3, 7	Model with AR lags p=1,2,3
Estimates of lag coefficients[a]		
μ	-0.0002	-0.0002
	(-0.92)	(-0.93)
Δy_{t-1}	0.162**	0.16027**
	(2.21)	(2.05)
Δy_{t-2}	0.290***	0.26407***
	(3.95)	(3.42)
Δy_{t-3}	-0.256***	-0.25171***
	(-3.46)	(-3.21)
Δy_{t-7}	0.270***	
	(3.78)	
Goodness of Fit Measures		
Standard Error Estimate	0.001727	0.001797
AIC	-1728.97	-1713.95
SBC	-1662.27	-1640.9
Ljung-Box Q-statistic[b]		
Q(6)	3.48	2.38
	(0.176)	(0.498)
Q(12)	6.30	13.31
	(0.613)	(0.149)
Q(18)	10.96	20.13
	(0.690)	(0.167)

* Indicates significance at the p=0.10 level

** Indicates significance at the p=0.05 level

*** Indicates significance at the p=0.01 level

[a] t values are in parentheses
[b] p values are in parentheses

Table 5. Maximum Likelihood Estimation for Change in the Proportion of Restructured Loans Δy_t with Outliers

Parameter	Estimate	Standard Error
μ	-0.0002	0.0002
Δy_{t-1}	0.1738***	0.0772
Δy_{t-2}	0.2653***	0.0765
Δy_{t-3}	-0.2559	0.0777
October 1997	-0.0003	0.0018
November 1997	0.0015	0.0018
December 1997	0.0057***	0.0019
January 1998	0.0051***	0.0019
February 1998	0.0023	0.0019
March 1998	0.0086***	0.0019
April 1998	0.0053***	0.0019
May 1998	0.0032**	0.0019
June 1998	0.0009	0.0019
July 1998	-0.0023	0.0019
August 1998	-0.0027	0.0018
September 1998	-0.0012	0.0018
$\text{Outlier}_{\text{May1994}}$	0.0144***	0.0018
$\text{Outlier}_{\text{December1994}}$	0.0059***	0.0017
$\text{Outlier}_{\text{December2002}}$	-0.0118	0.0017
$\text{Outlier}_{\text{March2008}}$	0.0111***	0.0017
Number of Residuals	177	
Standard Error	0.0018	

Ljung-Box Q-statistic[a]	
Q(6)	2.38
	(0.498)
Q(12)	13.31
	(0.149)
Q(18)	20.13
	(0.167)

* Indicates significance at the p=0.10 level, one-tailed test; ** Indicates significance at the p=0.05 level, one-tailed test; *** Indicates significance at the p=0.01 level, one-tailed test
[a] p values in parentheses

Table 6 Immediate and Total Effects on the Change in Proportion of Restructured Loans of the 1998 El Niño by Month

Month	Immediate Effect c (%)	95% Confidence Intervals c (one-tailed test, %)[9]	Total Effect (%)
December 1997	0.57	0.22-0.88	0.78
January 1998	0.51	0.20-0.82	0.70
March 1998	0.86	0.55-1.17	1.17
April 1998	0.53	0.22-0.84	0.72
May 1998	0.32	0.01-0.63	0.44
Cumulative Total Effect			3.81

[9] $0.95 = P(c - 1.64 * se \leq C \leq c + 1.64 * se)$
where *c* is the effect in the sample, *C* is the actual effect, and *se* is the standard error of the estimate

Figure 1. Effects of Correlated Risk on the Lending Portfolio

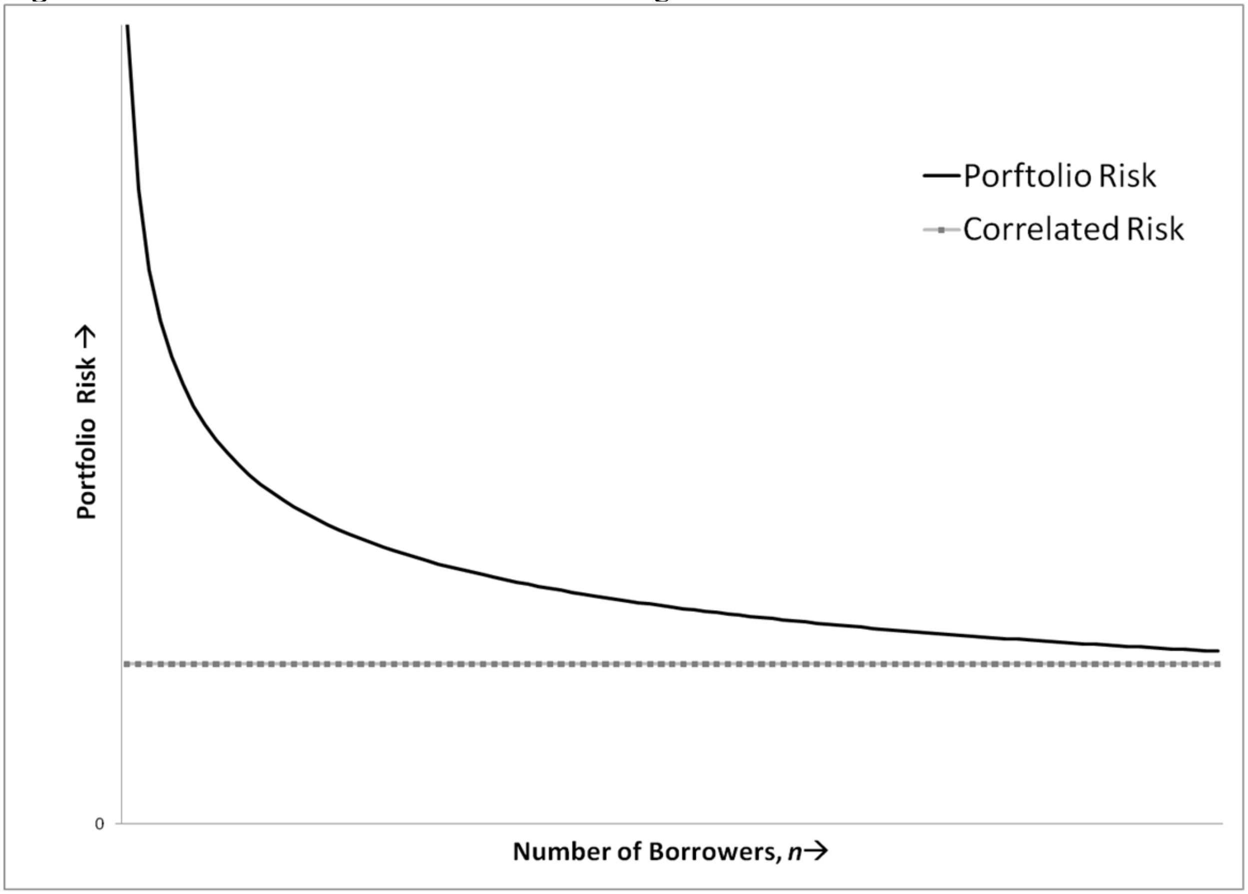

Figure 2. Proportion of Restructured Loans by Month from January 1994 to October 2008

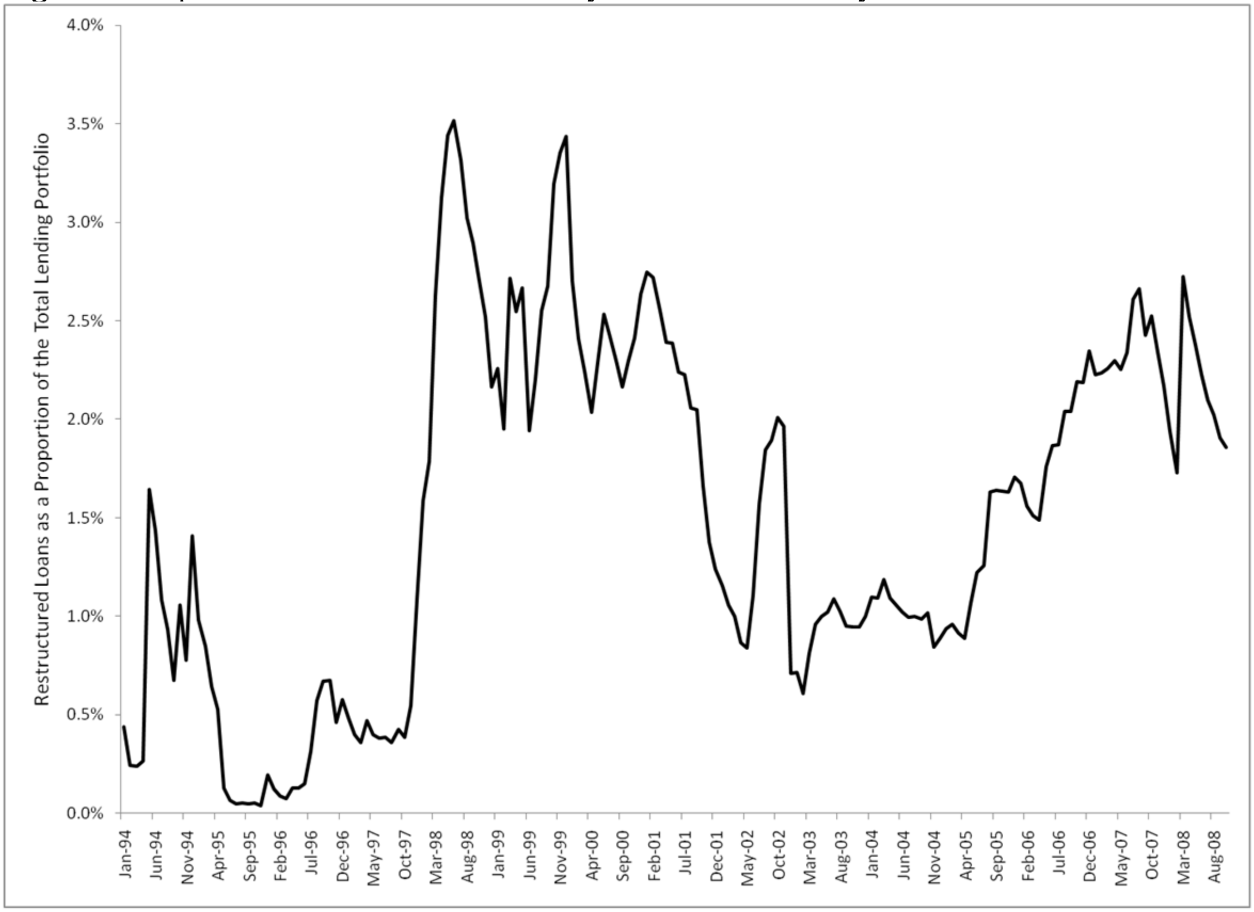

Figure 3. Proportion of Late Loans by Month from January 1994 to October 2008