Loan Portfolio Performance and El Niño, an Intervention Analysis

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Loan Portfolio Performance and El Niño, an Intervention Analysis

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 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 the productivity of capital is so high for banks, holding larger-than-necessary capital reserves can represent significant opportunity costs for lenders (Greuning and Bratanovic, 2009).

This article is focused on accurately estimating a natural disaster risk because the results of risk assessment have broad implications for the business strategies a financial institution adopts. The statistical methods used here are but one aspect of a risk assessment, as this raw information about the past event would need to be adapted based on expectations regarding how the risk or exposure of the financial institution has changed. Risk assessment is a crucial first step in identifying more efficient and effective strategies. Risk transfer such as through insurance may be one important risk management strategy that could reduce the cost of managing a natural disaster relative to the other strategies currently implemented by a financial institution. More efficient and effective disaster risk management should ultimately reduce costs of and increase access to financial services for users. In the conclusion of this article, we specifically consider how its findings might inform the development and implementation of an insurance-like mechanism that would allow a financial institution to secure and grow its business in disaster-prone regions.

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 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 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 analysis 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 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 tree 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 Niño 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 credit constraints including by lowering interest rates in Piura would raise regional output by 26 percent. Thus, understanding more about how El Niño risk affects the financial sector is extremely important to facilitate more efficient risk management that improves 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 financial institution in Piura, Caja Piura. The data for these analyses can be downloaded from the website of the banking regulator in Peru, Superintendencia de Banca, Seguros y AFP (called SBS hereafter, http://www.sbs.gob.pe/portalSBS/). SBS posts key balance sheet variables for each financial institution. 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 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.

Regarding independent variables, dummy variables are used to identify the months before, during, and after the El Niño event. [2] Catastrophic flooding began in February of 1998 and continued through approximately April; 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 July of 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 November 1997 through July 1998 for the analyses of restructured loans, three months before and after the event.

[2] 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. 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.

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.

Several control variables are also included in the model: inflation, commodity prices for the most extensively grown crops, and crude oil prices. Regarding inflation, we use monthly consumer price index data for Lima (which is roughly 500 miles from Piura).[3] Because the bank data available from the regulator are at the portfolio level, identifying additional, suitable control variables is difficult. Caja Piura reports that roughly 20% of the credit portfolio was agricultural credits before the 1997-1998 El Niño. The major agricultural commodities produced in Piura from 1994 to 2008 were cotton, rice, bananas, mangoes, and a Peruvian variety of yellow corn (Trivelli, 2006). While agriculture is only a fraction of the overall portfolio, the importance of agriculture to the regional economy may make these commodity prices important to include in evaluating the credit portfolio. Regional, monthly commodity prices are not publicly available for these crops; however, international, monthly prices for cotton, rice, and bananas are available

[3] Inflation data downloaded from the Central Reserve Bank of Peru (http://www.bcrp.gob.pe) and is in 2009 U.S. dollars.

and are included in the model.[4] While Piura has an active export market, it is unclear the extent to which regional prices for these commodities are co-integrated with international prices. Oil prices can have both immediate effects based on gasoline prices and lagged effects based on forward contracts for fertilizer producers and others. Regional, monthly fertilizer prices are unavailable for 1994-2008, and these lagged effects are often industry-specific and are unknown to the authors. Of course, gasoline prices affect many types of firms (e.g., Caja Piura reports holding notable portions of their credit portfolio in the fishery and transportation sectors); therefore, we include international, monthly crude oil prices, attempting to capture the immediate effects of oil prices.[5] As a result, the general form of the model is

$$y_t = \mu + \gamma AR + \theta MA + aC + bD + \epsilon_t$$

where y_t is the dependent variable, μ is the intercept term, AR denotes autoregressive terms, MA denotes moving average terms, C is a vector of control variables, D is a vector of dummy variables identifying the El Niño event, and ϵ_t is the error term.

Estimation Procedures

Testing 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. 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). 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

[4] Commodity price data downloaded from Index Mundi (http://www.indexmundi.com).
[5] Crude oil price data downloaded from Index Mundi.

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 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.

If the effect of El Niño 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. 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. 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. We include four outliers with an inclusion criteria that their values must deviate from the mean with significance level of $\alpha < 0.01$.[6]

We use a maximum likelihood estimation to assess the effects of the El Niño dummies on the restructured loans and/or late loans. We only analyze the effects for the event dummies that are significant in the hypothesis testing stage, the first stage *before* the outliers are omitted. The *immediate* effects of the 1997-98 El Niño are estimated by the magnitude of the coefficients for the event dummies (Enders, 2004). For example, consider a model with a one period autoregressive (AR) lag

$$y_t = \mu + \gamma_1 y_{t-1} + aC + bD + \epsilon_t$$

The immediate effect of the event is the coefficient vector of the dummy variables b.

The *long-term* effects of the event can be analyzed using 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

$$y_{t+1} = \mu + \gamma_1 y_t + aC + bD + \epsilon_{t+1}$$

by substitution for y_t

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

Thus, when shocks associated with the event enter the model, their total effects must be

[6] 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).

estimated using the AR terms specified in the time-series model. For example, for the model with one AR lag

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

where j represents 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., $\Delta y_t = y_t - y_{t-1}$) 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 autocorrelation function (ACF) and partial autocorrelation function (PACF) and the model fit statistics indicate an AR lag structure with a lag at the third (Δy_{t-3}), sixth (Δy_{t-3}), and seventh (Δy_{t-7}) periods and no moving average (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, and April 1998, reported in Table 2. Significant effects in December and January indicate loans were being restructured *before* the catastrophic flooding due to El Niño, which began in February 1998. Significant effects in March and April 1998 coincide with the major period of flooding due to El Niño. By May 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 from May onward.

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. A significant decrease in the proportion of late loans occurs during December 1997. The control variables (inflation and international prices of crude oil, bananas, cotton, and rice) had no significant effect on the proportions of late or restructured loans.

Testing indicates El Niño did not significantly increase 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. The significant decrease in late loans in December 1998 is likely at least partially explained by a restructuring of some of late loans as it coincides with an increase in the proportion of restructured loans. Additionally, the decrease in late loans may be due to loans going the judicial collections process.

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. We shared these results with Caja Piura and they confirmed that they prepared their loan portfolio for El Niño based on forecasting signals. In this fashion, the bank 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 is likely 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.

The lack of significance regarding the control variables is worthy of discussion. From 1994 to 2008, inflation was relatively low and stable; thus, it may be no surprise that this variable did not affect loan performance. The result of no effect in terms of agricultural commodity prices and oil prices is surprising. There were spikes in these prices (e.g., rice prices were quite low in the northern hemisphere spring and summer of 2001, and oil prices reached historic highs in the summer of 2007). It may be an indication that regional prices are not well integrated with international markets, that oil and agricultural commodity prices affect some borrowers but not to a degree that causes problems significant at the portfolio level, or perhaps most likely, lag effects between the control variables and the dependent variables occur but are not included in the model.

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 financial institutions did not respond directly to these dates but noted significant outliers are largely due to policy changes (both government policies and policies internal to the bank). Identifying the effects of a new policy on the portfolio performance is particularly challenging (e.g., there may be some lag effect between when the policy is implemented and when the policy affects loan repayments).We note here that the purpose of controlling outliers is to enhance the risk assessment process — that is, our purpose is to isolate El Niño effects from the normal variability of financial operations for Caja Piura. Omitting outliers is consistent with this goal, especially because these outliers are so disruptive to the dependence order (the AR and MA components) of the time series. While omitting outliers aids our objective, it certainly results in a less generalizable model that has limited use outside of our purpose. Likewise, we should note that the dependence orders identified for the models in this paper are likely context-specific due to the El Niño and the limited ability of the control variables to add explanatory power. As a result, the model may be unstable and, therefore, not appropriate for other purposes such as forecasting.

The time-series process was again tested and several autoregressive structures were compared. The analyses indicated no MA terms should be included and the best-fitting, parsimonious model includes AR lags for the first, second, and third periods. Thus, the model is

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

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 4. 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, and April 1998. The largest immediate effect is seen in March 1998 when the proportion of restructured loans increases by 0.89 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

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

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 $\gamma_i^k b$ 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 5.[7] These analyses indicate El Niño had a total cumulative effect of 3.6 percent, that is, the proportion of restructured loans increased by 3.6 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 3.6 percent of the 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 618 percent increase in restructured loans if the loans never matured and the bank took no further action to minimize losses.[8] 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

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

[8] 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 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 3.6 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 618 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 the 1997-98 El Niño was PEN 1.96 million (about USD 737,000 in 1997 dollars),[9] roughly equivalent to one year's profits for this financial institution (e.g., average annual profits for 1994-1996 were PEN 1.6 million).[10]

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 strong example of this exposure. These findings are worthy of careful consideration by regulators managing MFIs as they may challenge the

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

[10] Average annual profits from 1994-1996 were PEN 1.6 million. It should be noted that the estimate of the effect on restructured loans is a starting point, a regulatory tool indicating a portion of the portfolio that is of lower quality. Additional information is needed to estimate the consequential costs and losses associated with holding lower quality loans (e.g., the probability of default and loss given default for loans that are restructured, the duration of these restructured loans, effects on the capital base, etc.).

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.[11] 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 around the world 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 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

[11] Two approaches under Basel II require basing capital requirements for operational risk on gross income: the Standardized Approach and the Basic Indicator Approach (BCBS 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.

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 loan maturity 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 including in helping the community rebuild after the event. 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 non-repayment that contribute to longer term credit constraints.

These conclusions motivate the advancement of risk transfer mechanisms such as insurance that MFIs could purchase to protect their portfolios. We consider three alternatives. First, a portfolio-level credit guarantee could be designed that insures against the level of late and/or restructured loans exceeding a certain portion of the portfolio. In this case, the rate-making for the insurance could include modeling the effect of El Niño on poorly performing loans to some distribution (e.g., the negative binomial for modeling the frequency, and negative exponential for modeling intensity/duration). [12] Given the importance of management decisions highlighted in this paper, such an insurance would require risk-sharing mechanisms (such as co-insurance) to reduce moral hazard; however, even with risk-sharing, an insurer offering this product may have to take significant monitoring steps to present moral hazard that could increase the price of the insurance.

Second, alternative to a portfolio-level credit guarantee, an index insurance based on an indicator of the natural disaster could be purchased by the financial institution to transfer its portfolio risk. In Peru, an index insurance against El Niño is now being offered. The El Niño insurance bases payouts on sea-surface temperature off the coast of Peru, which is a strong predictor of El Niño (Khalil *et al*., 2007). This index insurance has the benefit of avoiding moral hazard problems associated with the credit-guarantee approach; however, relative to a loan portfolio guarantee, it has the drawback of higher basis risk, differences between insurance payouts based on sea-surface temperature and the actual losses and increased costs the MFI incurs due to El Niño.

Third, a household-level insurance could be offered. This microinsurance could be either a credit guarantee or an index insurance (e.g., the El Niño index could be sold bundled with a loan). Offering insurance to households provides the benefit of some protecting MFI users; however, the most important benefit for the MFI is that (unlike portfolio-level insurance) microinsurance would reduce default rates when explicitly tied to loans (e.g., households agree to pay off outstanding loans with an index insurance indemnity). A significant challenge to a

[12] We thanks Dr. Calum Turvey for his conceptual contributions here.

micro-level loan guarantee is that the cost of monitoring is substantially higher than at the portfolio-level and may make it all but impossible to offer a micro-level loan guarantee that is affordable but not riddled with moral hazard problems. A significant challenge to micro-level index insurance is that basis risk will be higher for household level products than for portfolio-level products (Collier *et al.*, 2010). Beyond these specific challenges, experience in microinsurance markets indicates that market development and growth is a slow process, tending to result in low market penetration even after several years of offerings. As a result, optimally protecting financial institutions may require some blend of household and portfolio-level insurance with a strong emphasis on the portfolio-level as microinsurance markets develop.

Whatever approach, more explicit modeling of the actual cost to the MFI of the poor loan performance is needed. This modeling should include both increased costs and losses (e.g., increased administrative costs, increased holdings of specific provisions, and increased loan defaults) but also opportunity costs (e.g., cost of holding capital in poorly performing loans) that might be avoided if the MFI could transfer its risk. Modeling can also provide benefits to microinsurance development as it may motivate MFIs to target incentives (e.g., lower interest rates) to households in order to increase microinsurance uptake. We are in the process of developing these models.

Important follow-up analyses could also 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.

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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=0.1 level; *** 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

Parameter	**Estimate**	**Standard Error**
μ	0.000	0.000
Δy_{t-3}	-0.262***	0.079
Δy_{t-6}	-0.193**	0.077
Δy_{t-7}	0.156**	0.076
ΔCPI_t	0.000	0.001
Δoil_t	0.000	0.000
$\Delta banana_t$	0.000	0.000
$\Delta cotton_t$	0.000	0.000
$\Delta rice_t$	0.000	0.000
November 1997	0.001	0.002
December 1997	0.007***	0.002
January 1998	0.006**	0.002
February 1998	0.002	0.003
March 1998	0.009**	0.003
April 1998	0.004*	0.003
May 1998	0.003	0.002
June 1998	0.000	0.002
July 1998	-0.002	0.002
Number of Residuals	177	
Standard Error	0.0025	

Ljung-Box Q-statistic[a]	χ^2	p value
Q(6)	2.93	0.40
Q(12)	6.31	0.71
Q(18)	7.85	0.93

*Indicates significance at the p=0.1 level; ** Indicates significance at the p=0.05 level; *** Indicates significance at the p=0.01 level

[a] Periods lagged in parentheses

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

Parameter	**Estimate**	**Standard Error**
μ	0.000	0.000
Δl_{t-7}	-0.263***	0.079
ΔCPI_t	0.000	0.001
Δoil_t	0.000	0.000
$\Delta banana_t$	0.000	0.000
$\Delta cotton_t$	0.000	0.000
$\Delta rice_t$	0.000	0.000
June 1997	-0.001	0.005
July 1997	0.004	0.005
August 1997	0.010*	0.005
September 1997	0.002	0.005
October 1997	0.006	0.005
November 1997	-0.001	0.005
December 1997	-0.016***	0.005
January 1998	0.006	0.005
February 1998	0.004	0.005
March 1998	0.000	0.005
April 1998	0.004	0.005
May 1998	-0.006	0.005
June 1998	0.001	0.005
July 1998	0.001	0.005
Number of Residuals	177	
Standard Error	0.005	
Ljung-Box Q-statistic[a]	χ^2	p value
Q(6)	3.07	0.69
Q(12)	5.38	0.91
Q(18)	17.94	0.39

*Indicates significance at the p=0.1 level; *** Indicates significance at the p=0.01 level

[a] Periods lagged in parentheses

Table 4. Maximum Likelihood Estimation for Change in the Proportion of Restructured Loans Δy_t with Outliers

Parameter	**Estimate**	**Standard Error**
μ	0.0000	0.0002
Δy_{t-1}	0.1551**	0.0786
Δy_{t-2}	0.2758***	0.0773
Δy_{t-3}	-0.2554***	0.0789
ΔCPI_t	-0.0007	0.0005
Δoil_t	0.0002*	0.0001
$\Delta banana_t$	0.0000	0.0000
$\Delta cotton_t$	0.0000	0.0000
$\Delta rice_t$	0.0000	0.0000
November 1997	0.0015	0.0018
December 1997	0.0065***	0.0018
January 1998	0.0058***	0.0019
February 1998	0.0030	0.0019
March 1998	0.0089***	0.0019
April 1998	0.0052***	0.0020
May 1998	0.0029	0.0019
June 1998	0.0018	0.0018
July 1998	-0.0013	0.0018
$\text{Outlier}_{\text{May1994}}$	0.0143***	0.0017
$\text{Outlier}_{\text{December1994}}$	-0.0120***	0.0017
$\text{Outlier}_{\text{December2002}}$	0.0121***	0.0018
$\text{Outlier}_{\text{March2008}}$	0.0062***	0.0017
Number of Residuals	177	
Standard Error	0.0017	

Ljung-Box Q-statistic[a]	χ^2	p value
Q(6)	2.99	0.39
Q(12)	12.83	0.17
Q(18)	16.97	0.32

*Indicates significance at the p=0.1 level; ** Indicates significance at the p=0.05 level; *** Indicates significance at the p=0.01 level

[a] Periods lagged in parentheses

Table 5. 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 (%)[13]	Total Effect (%)
December 1997	0.65	0.30-1.00	0.88
January 1998	0.58	0.21-0.95	0.79
March 1998	0.89	0.52-1.26	1.21
April 1998	0.52	0.13-0.91	0.71
Cumulative Total Effect			3.59

[13] $0.95 = P(c - 1.96 * se \leq C \leq c + 1.96 * se)$
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

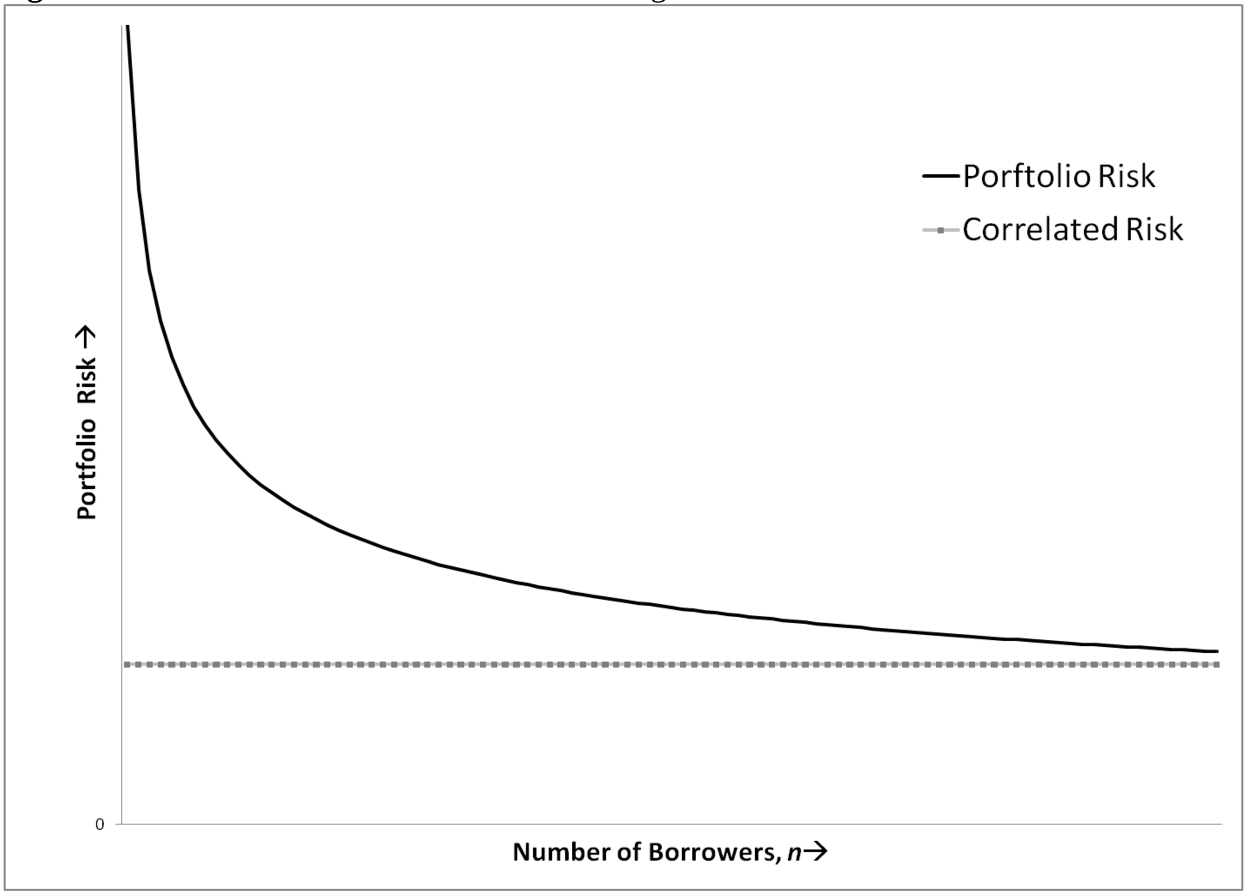

Figure 2. Proportion of Restructured Loans by Month from January 1994 to October 2008

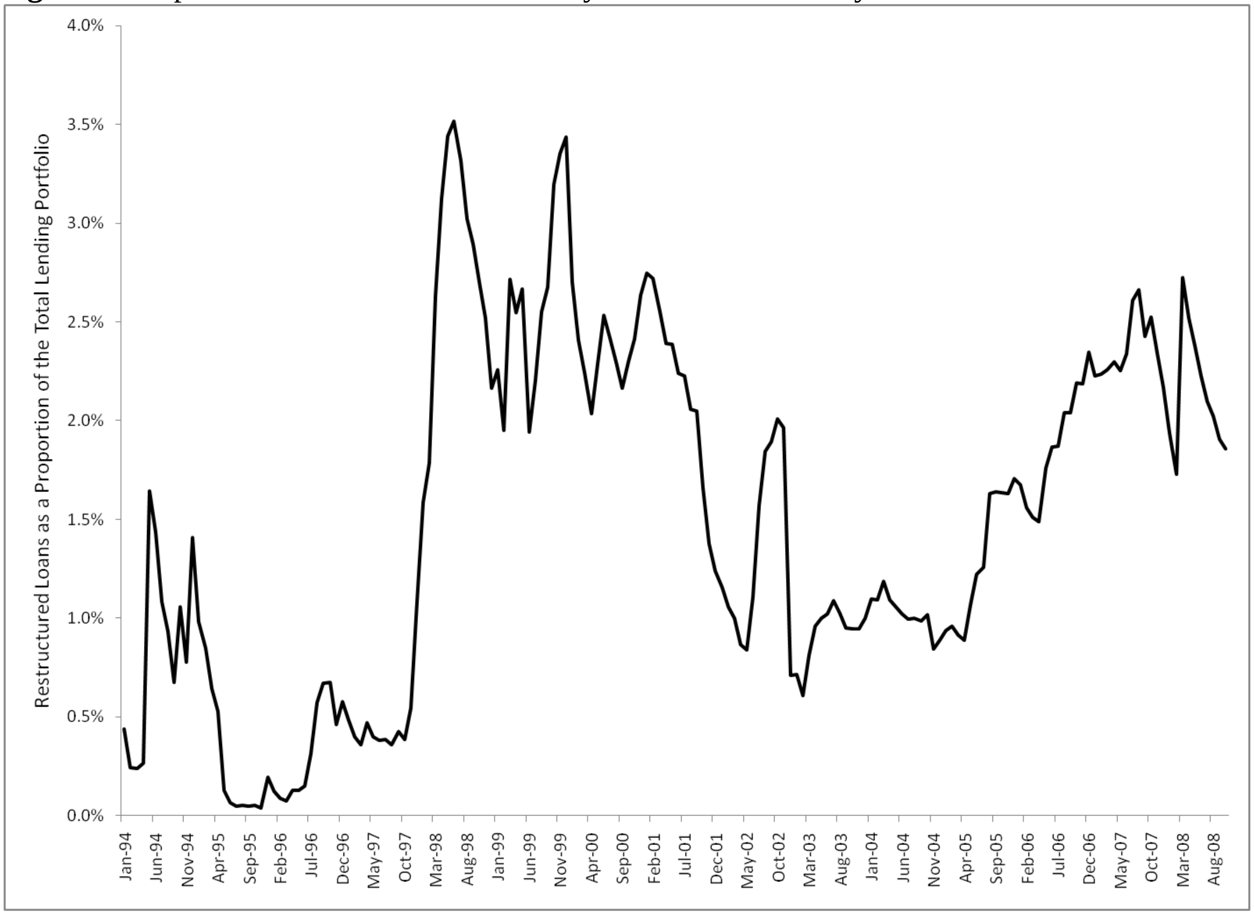

Figure 3. Proportion of Late Loans by Month from January 1994 to October 2008