Loans Growth and Banks' Risk: New Evidence

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Abstract

This study provides new evidence on the relationship between abnormal loan growth and banks' risk taking behavior, using data from a rich panel of Colombian financial institutions. We show that abnormal credit growth during a prolonged period of time leads to an increase in banks' riskiness, supported by a reduction in solvency and an increase in the ratio of non-performing loans to total loans. We also show that abnormal credit growth played a fundamental role in the bank-failure process during the late 1990s financial crisis in Colombia. Our results have important implications for financial regulation and macro-prudential policy.

JEL Classification: G20; G21

Keywords: Abnormal loan growth; Hazard duration models; FGLS estimation; Emerging market economies.

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1. Introduction

An important conclusion of modern economic theory is that finance is good for growth (Cecchetti and Kharroubi, 2012). However, despite the well-known advantages of credit markets development and growth for the economy in the long-run, episodes of excessive loan growth may have negative effects on the financial system and the economy at large.

The history of financial crises and particularly the recent international financial crisis, clearly illustrate what can go wrong with excessive credit growth. There is abundant empirical literature documenting that many scenarios of financial crises have been preceded by episodes of abnormal credit growth that lead to the development of asset price bubbles. In fact, Borio and Lowe (2002) and Borio (2009) show that excessive credit growth is the main leading indicator of a financial crisis in a twelve-month horizon.

This scenario may happen if during expansionary periods, banks, firms and households tend to underestimate risk, taking actions that increase their probability of experiencing financial difficulties in the future (see, for example, Altunbas et al 2010 and 2012). Some authors have related this pattern to myopic behavior of private agents (García-Suaza et al, 2012; and, Borio et al, 2001) and others have highlighted the presence of asymmetric information and financial frictions in credit markets (Holstrom and Tirole, 1997; and, Mendoza and Bianchi, 2010).

Nonetheless, there are many reasons explaining why individual banks expand their balance sheets, and credit expansion does not necessarily imply more risk for banks. For instance, banks may be interested in diversifying their loan portfolio or cross-selling. Banks may try to seize new profitable lending opportunities and expand geographically, obtaining a better diversification of risks. From a policy maker's perspective, it is crucial to disentangle the effects of a bank's balance-sheet expansion on its future financial health. Hence, it is imperative to identify whether loan growth is being accompanied by adequate risk management from a microeconomic perspective.

There are some recent papers that study the relationship between credit growth and the posterior performance of banking sectors' financial indicators from an aggregate perspective (Dell'Ariccia et al, 2008; Demyanyk and Van Hemert, 2011; and, Gorton, 2009). Despite the relevance of studying the relation between credit growth and banks' performance, there are relatively few works that study this major topic from an individual institutions' perspective (e.g., Laeven and Majmoni, 2003; Berger and Udell, 2004). The intertemporal relation between loan growth and banks' risk taking behavior has not been exploited yet (an exception is the recent study by Foos, Norden and Weber, 2010). Up to our knowledge, there are no studies of this kind for banks in an emerging economy.

In this paper we study the relationship between abnormal loan growth and banks' risk taking behavior using information on individual Colombian banks' balance sheets between June 1990 and March 2011. We perform two different empirical exercises. On the one hand, we test the incidence of abnormal loan growth on banks' survival probability using information on individual banks' characteristics during the financial crisis of the late 1990s. On the other hand, we test the effect of abnormal loan growth on banks' financial health (solvency, non-performing loans and profitability), using cross-sectional time-series data on Colombian financial institutions between 1990 and 2011.

Our results show that abnormal loan growth is positively and significantly associated with non-performing loans, and negatively and significantly related with bank solvency. More importantly, we find a significant and positive impact of abnormal loan growth on the conditional probability of failing after a strong negative shock affecting the financial system at large. Thus, we provide evidence showing that during periods of accelerated credit expansion banks undertake higher risks that affect negatively the soundness of the financial system. This result calls for policy actions, such as implementing time-varying minimum capital requirements or imposing levies on abnormal loan growth to individual financial institutions.

The contributions of this document to the banking and finance literature are three-folded. First, up to our knowledge this is the first paper studying the relationship between credit growth and banks' risk-taking behavior using micro data for an emerging, bank-dependent economy. Second, our empirical methodology allows for studying the time-horizon in which the presence of abnormal credit growth affects the financial performance of banking institutions in Colombia. And third, this is the first study reporting evidence on the effect of abnormal loan growth on the conditional probability of failing during times of financial distress. We benefit from the use of an especially informative dataset of financial institutions covering a time span during which two complete financial cycles occurred.

The remainder of this paper is organized as follows. Section 2 presents a brief review of related literature. In Section 3 we describe the data used for our empirical analysis. In Section 4 we present our survival analysis results. In Section 5 we show the cross-sectional time-series results. And finally, in Section 6 we conclude.

2. Literature Review

Banking credit is an essential source of funding for both firms and households. If all agents had identical and complete access to perfect capital markets, the agents' financial structure would be irrelevant for investment decisions because internal and external funds would be perfect substitutes. However, there's an extensive economic literature, based on the seminal paper of Fazzari, Hubbard and Petersen (1988), showing that internal and external capital are far from being perfectly substitutable. Moreover, depending on individual characteristics, there is a hierarchy for each individual's access to external sources of funding. For instance, differences in cash flows and size affect firms' access to capital markets significantly (see, for instance, Gourio and Miao, 2010). In fact, as shown by Kashyap et al (1993), small firms and firms with low levels of cash flows have very limited access to capital markets and rely almost entirely on banking credit as their only source of external funding. These constraints appear to be stronger in emerging market economies with underdeveloped capital markets, in which informational imperfections abound. Similarly, differences in wealth and income affect households' access to external funding significantly. Low income households and households with a low level of wealth accumulation (young households and poor households) have very limited access to credit (Hurst and Lusardi, 2004).

Given that banking credit is the main source of external funding in most economies (this is especially true for the case of bank-based economies such as Germany, France, Japan and Colombia), and may be the only source of funding for many firms and households, credit availability and sound credit flows are essential for the development of investment projects and refinancing. Moreover, endogenous growth theory postulates a positive impact of financial deepening and credit growth on economic activity indicators in the long-run (Bencivenga and Smith, 1991). This hypothesis has been tested and confirmed by several empirical studies, such as Mishkin (2001), Levine (2001), and Bekaert, Harvey and Lundblad (2001).

Nevertheless, there is a downside of excessive credit expansions. The history of financial crises and particularly the recent international financial crisis, clearly illustrate what can go wrong with disproportionate credit growth. There is abundant empirical literature documenting that many scenarios of financial crises have been preceded by episodes of abnormal credit growth that lead to the development of asset price bubbles. In fact, Borio and Lowe (2002) and Borio (2009) show that excessive credit growth is the main leading indicator of a financial crisis in a twelve-month horizon.

The 2007 - 2008 international financial crisis has triggered a revitalized interest in understanding the role of credit in the economy. One of the main interests has relied in the relation between credit growth and financial crises. Recent literature supports the findings of the early warning tradition (e.g. Kaminsky and Reinhart, 1999; and, Goldstein, Kaiminsky and Reinhart, 2000), showing that not only financial crises are typically preceded by credit booms gone bust (Schularik and Taylor, 2012; and Jorda, Schularik and Taylor, 2011), but also that excessive credit growth is the main predictor of financial distress over a twelve-month time-window (Borio and Lowe, 2002; Borio, 2009; Tenjo and López, 2010; and, Alessi and Detken, 2011).

Despite the striking evidence on the importance of abnormal credit growth on financial stability from a macroeconomic perspective, there is very limited evidence of this relation from a microeconomic stand-point.

In an early study with individual US bank data, Sinkey and Greenwald (1991) showed that excessive past loan growth is positively associated with current loan losses. An interesting feature is that they found that there is substantial cross-sectional variation in this link. More recently, Laeven and Majnoni (2003) study this link indirectly, using Bankscope data for 45 countries. They found that bank provisions behave counter-cyclically and that there is a negative and significant contemporaneous relation between loan growth and loan losses. Bikker and Metzemakers (2005) found similar results using banking data for a sample of OECD countries during the period 1991 – 2001. There are other papers studying this relation for transition and developing economies that obtain comparable results (Kraft and Jankov, 2005; and, Cotarelli et al, 2005).

All the papers mentioned before abstract from the time-dimension of the relation between loan growth and individual banks' performance. There are other recent papers studying this issue. Salas and Saurina (2002) found that loan growth of Spanish savings banks is positively and significantly associated with loan losses three to four year later. In a recent study, Foos et al (2010) present a similar study Bankscope data for banks of sixteen developed economies, and found that abnormal loan growth leads to an increase in loan losses and a decrease in banks' solvency about three years later.

There are no papers studying the intertemporal relation between loan growth and individual banking performance for emerging market economies. Moreover, there are no studies on the relationship between abnormal loan growth and bank failure. This paper tries to fill this gap in the literature, providing evidence of these links for Colombia.

3. The data

We use balance-sheet data from 64 financial institutions, provided by Colombia's Financial Superintendence (the country's financial oversight organism) covering the period June 1990 - March 2011. Our sample includes 42 banks and 22 financial corporations. All institutions with at least 48 months of reported data and with no significant missing data were included. As of March 2011, this sample covers over 90% of Colombia's financial system's total assets, so it can be regarded as representative of the Colombian financial system at large.

Our main interest relies on identifying the intertemporal effects of loan growth on individual financial institutions' performance. Following previous studies (particularly Foos et al., 2010) abnormal credit growth, ALG_{it}, is defined as the difference between institution $i's$ annual loan growth rate at period t and the median[5] of all institutions annual loan growth rate at t. Defining abnormal credit growth this way we are able to control for the effect of the prevailing macroeconomic conditions on banks' willingness to extend new loans, and focus on the cross-sectional differences at each point in time. For the sake of robustness, we used alternative percentiles of the distribution of loan growth in defining ALG_{it}. However, as results were qualitatively identical under all different definitions, in the rest of the paper we report results using the median only.

We implement two different empirical exercises, to answer two different (but related) questions. On the one hand, we test the incidence of abnormal loan growth on banks' survival probability using information on individual banks' characteristics during the financial crisis of the late 1990s. On the other hand, we test the effect of abnormal loan growth on banks' financial health (solvency, non-performing loans and profitability), using cross-sectional time-series data on Colombian financial institutions between 1990 and 2011.

First, we use a duration or hazard function model to study the time to failure of financial institutions during the Colombian financial crisis. This methodology enables us to answer questions that are relevant both for financial supervisors and financial institutions, such as: Does abnormal credit growth affect significantly the probability of failing after a financial shock? Does the amount of time during which an institutions' loans portfolio expanded affect the probability of failing?

Since we are interested in time to failure during the financial crisis, the period of observation for the first empirical exercise is the 42 months elapsed from June 1998, the moment in which the crisis began (see Gómez-González and Kiefer, 2009), and December 2001, when the system started recovering. Financial data as of June 1998 was collected for each of the 54 institutions considered for this empirical analysis. Following previous studies and theoretical expectations, the following financial rations were considered in the explanation of time to failure: average abnormal loan growth (ALG_i^j), calculated as the j-months (prior to June 1998) average of ALG_{it}, where j takes on different values, such as 1

[5] We use the median rather than the mean of the growth rate of all institutions at a given point in time because our data is highly dispersed and for every given point we find several extreme values.

month, 12 months, 24 months, 36 months, and 48 months; solvency (CAP_i), defined as the ratio of tier 1 and tier 2 bank capital to risk-weighted assets; bank size ($SIZE_i$), defined as the assets of institution i divided by total system's assets; gross profit margin ($PROF_i$); asset quality (NPL_i), calculated as the ratio of non-performing loans to total loans; asset composition ($COMP_i$), defined as the percentage of assets represented by loans; and, a dummy variable ($BANK_i$) taking on value one when the financial institution is a bank and zero otherwise. The variable *COMP* can be interpreted as controlling for portfolio characteristics potentially related with volatility. This set of variables is similar to those used in traditional CAMEL models.

Regarding failure, from the group of institutions 12 failures were observed between June 1998 and December 2001, representing a failure rate of 24%, and an average failure rate of 0.9% per-period.

Second, we use cross-sectional time-series models to study the relation between abnormal credit growth and financial institutions' health using quarterly data between June 1990 and March 2011. We estimate three groups of models: one for solvency, one for non-performing loans, and one for profitability. Solvency and non-performing loans correspond to CAP_{it} and NPL_{it}, respectively, as defined above. Profitability, ROA_{it}, corresponds to the traditional indicator of asset profitability. These sets of estimations are performed to identify the channels through which abnormal loan growth affects banks' financial health.

Expansions of loan portfolio can be financed either issuing new debt or issuing new capital. If these expansions are financed issuing new capital, the effect of loan growth on solvency should be negligible or even null. If, on the contrary, credit expansion is financed with additional debt, the impact of abnormal loan growth on solvency should be negative and would imply a riskier behavior of banks.

As we mentioned above, credit expansions do not always imply future loan portfolio deterioration. If new loans are provided to solvent borrowers with profitable projects, there should be no significant impact of loan growth on the future ratio of non-performing loans to total loans. However, if new loans are extended to riskier customers or projects, an increase in this ratio is expected several months ahead.

Finally, we estimate the effect of cumulative abnormal loan growth on banks' profitability. Banks may be seeking for return when expanding their balance sheets and incurring on higher risks. We formally test this hypothesis studying the impact of abnormal loan growth on asset profitability.

In this second empirical exercise we exclude solvency as an explanatory variable and include instead an inverse leverage ratio (LEV_{it}). We also replace $SIZE_{it}$ for $(SIZE \times ALG)_{it}$, the interaction between size and abnormal credit growth. This change of regressor is done for stationarity purposes (while panel-data unit-root tests do not reject the null hypothesis of unit root for $SIZE_{it}$, they do so for the interaction variable). Additionally, we excluded $PROF_i$ and $LOAN_i$, and included $PROV_{it}$, the ratio of provisions to total loans.

4. Empirical results

In this section we present a quick overview of the two different empirical modeling strategies used in this study, together with the respective estimation results.

4.1 Duration models to study bank failure

We use a duration or hazard function model to study the time to failure of financial institutions. This approach generalizes the more common binary response (logit or probit) approach by modeling not only the occurrence of failure but the time to failure - allowing finer measurement of the effect of different variables on failure.

Most of the papers that apply these models to explain time to bank failure use the semi-parametric proportional hazards model of Cox (1972); an exception is the work of Carree (2003), who uses several parametric models to explain bank failure in Russia. The proportional hazards model is the most frequently used, because it does not make assumptions about the particular functional form of the baseline hazard, and because estimated hazard functions of bank failure in many cases are non-monotonic, thus reducing the number of parametric models that can be used.

In duration models, the dependent variable is duration, the time that takes a system to change from one state to another. In the case of bank failure, duration is the time that it takes for a bank to fail after the occurrence of a negative shock that affects the financial system. From a theoretical perspective, duration T is a non-negative, continuous random variable. However, in practice, duration is usually represented by an integer number of months, for example. When T can take a large number of integer values, it is conventional to model duration as being continuous.

Duration can be represented by its density function $f(t)$ or its cumulative distribution function $F(t)$. The survival function, an alternative way of representing duration, is given by $S(t) = 1 - F(t) = Prob(T > t)$. In words, the survival function represents the probability that the duration of an event is larger than a given *t*. The probability that a state ends between periods *t* and $t + \Delta t$, for Δt small and positive, given that it lasted up to time *t*, is given by

$$Prob(t < T \leq t + \Delta t | T > t) = \frac{F(t+\Delta t) - F(t)}{S(t)} \qquad (1)$$

This is the conditional probability that the state ends in a short time after *t*, provided it has reached time *t*. For example, in the case of bank failure it is the probability that a bank changes of state from operating to not operating (i.e. fails) in a short time after time *t*, conditional on the fact that the bank was still operating at time *t*.

The hazard function, $\lambda(t)$, which is another way of characterizing the distribution of T, results from considering the limit when $\Delta t \rightarrow 0$ of equation (1). This function gives the instantaneous probability rate that a change of state occurs, given that it has not happened up to moment *t*. The cumulative hazard function $\Lambda(t)$ is the integral of the hazard function. The relation between the hazard function, the cumulative hazard function and the survival function is given by equation (2):

$$\Lambda(t) = \int_{s=0}^{t} \lambda(s) ds = -log[S(t)] \qquad (2)$$

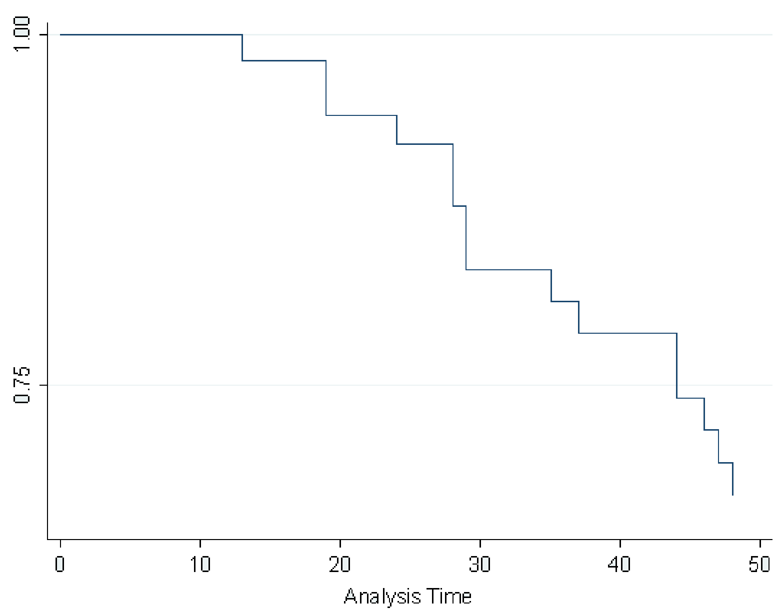
Some empirical studies use parametric models for duration. Commonly used distributions are the exponential, the Weibull and the Gompertz. The exponential implies a constant hazard while the Weibull admits decreasing or increasing hazards. The Gompertz distribution allows non-monotonic hazard rates, but is not particularly flexible. Further, the baseline hazard in our formulation reflects changes in macroeconomic conditions common to all the institutions. There is no reason to think these will correspond to a monotonic hazard, and indeed we find evidence it does not.

We begin by estimating the unconditional (raw: no covariates) survivor function, using the Kaplan-Meier non-parametric estimator, which takes into account censored data. Suppose that bank failure is observed at different moments in time, $t_1, t_2, \ldots, t_m$, and that d_i banks fail at time t_i. For $t \geq t_i$,

$$\hat{S}(t) = \prod_{t_i \leq t} \left[1 - \frac{d_i}{N_i}\right] \qquad (3)$$

Where N_i represents the total number of banks that were still operating at time t_i. Figure 1 shows the estimated survival function for the sample of financial intermediaries included in this study.

Figure 1: Kaplan-Meier Survival Estimate



The failure pattern of banks and of other financial institutions during the financial crisis of Colombia was similar in terms of percentage of institutions failing. That suggests that the survival functions of both groups might be similar. In order to corroborate that intuition, tests of equality of the survival functions were done. The results obtained from the Log-rank, Cox, and Wilcoxon tests give us confidence that pooling is appropriate, as can be there is no evidence to reject the null hypothesis of equality of the survival functions of both groups. Therefore, in the rest of the paper we treat all the institutions as one group.

In order to estimate the hazard function, it is first required to obtain an estimation of the cumulative hazard function. The Nelson-Aalen non-parametric estimator is natural for this purpose. Equation (4) shows how to compute this estimator. For $t \geq t_i$,

$$\widehat{\Lambda}(t) = \sum_{t_i \leq t} \frac{d_i}{N_i} \qquad (4)$$

The hazard function can be estimated as a kernel-smoothed representation of the estimated hazard contributions[6] $\Delta\widehat{\Lambda}(t_i) = \widehat{\Lambda}(t_i) - \widehat{\Lambda}(t_{i-1})$, as

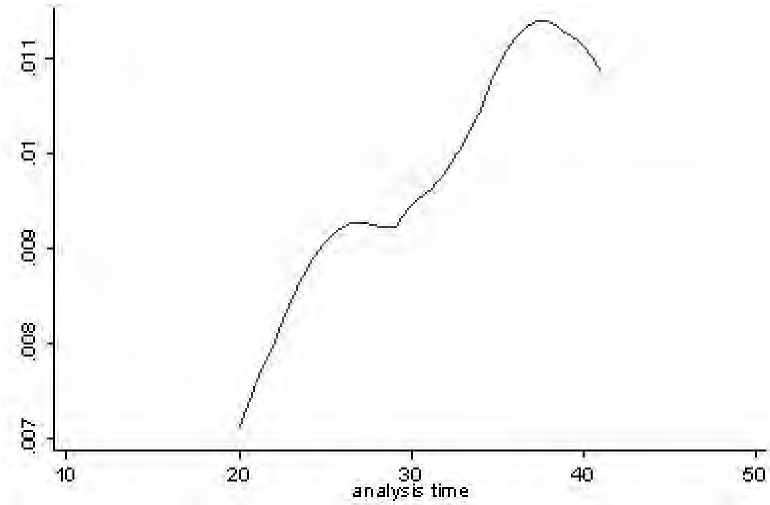
$$\hat{\lambda}(t) = \frac{1}{b} \sum_{i=1}^{D} K\left(\frac{t - t_i}{b}\right) \Delta\widehat{\Lambda}(t_i) \qquad (5)$$

where *K*( ) represents the kernel function, *b* is the bandwidth, and the summation is over the total number of failures *D* that is observed (Klein and Moeschberger, 2003).

Figure 2 shows the estimated smoothed-hazard function for the group of financial institutions. Note how the hazard rate of failure is clearly non-monotonic. This behavior of the baseline hazard reflects events applying to all institutions, like changes in macroeconomic conditions during the time of the study. Of particular importance, there was a change in the exchange rate regime in September 1999, from a crawling-peg system to a free floating system. The form of the estimated hazard function shows that the most commonly used parametric models for the distribution of duration do not seem to be appropriate for modeling the baseline hazard of bank failure in Colombia during the period of financial distress.

[6] The kernel-smoothed estimator of $\lambda(t)$ is a weighted average of these "crude" estimates over event times close to *t*. How close the events are is determined by *b*, the bandwidth, so that events lying in the interval $[t - b, t + b]$ are included in the weighted average. The kernel function determines the weight given to points at a distance from *t*. Here we use the asymmetric Epanechnikov kernel function.

Figure 2: Smoothed Hazard Function Estimate



Our objective is to understand how bank-specific variables affected the conditional probability of failure and time to failure after the shocks that initiated the financial crisis. In ordinary regression models, explanatory variables affect the dependent variable by moving its mean around. However, in duration models it is not straightforward to see how explanatory variables affect duration and the interpretation of the coefficients in these types of models depends on the particular specification of the model. But there are two widely used special cases in which the coefficients can be given a partial derivative interpretation: the proportional hazards model and the accelerated lifetime model (Kiefer, 1988).

Following the previous literature on the application of duration models to bank failure and building on the above analysis indicating that conventional candidates for parametric models are inappropriate, this paper estimates a proportional hazards model in which no parametric form is assumed for the baseline hazard function. As shown below using a specification test, this assumption seems to be appropriate for the problem of interest.

Under the proportional hazards specification the hazard rate can be written as:

$$\lambda(t, X, \beta, \lambda_0) = \lambda_0(t)\phi(X, \beta) \qquad (6)$$

where $\lambda_0(\cdot)$ is the baseline hazard. Note that the effect of time on the hazard rate is captured completely through the baseline hazard. One common specification for the function $(\cdot)$, which is followed in this paper, is $\phi(X, \beta) = \exp{(X'\beta)}$, where X is a vector of covariates and β is the corresponding vector of parameters to be estimated. Under this specification,

$$\frac{\partial log[\lambda(\cdot)]}{\partial x_k} = \beta_k \qquad (7)$$

for all k . Therefore, the coefficients can be interpreted as the constant, proportional effect of the corresponding covariate on the conditional probability of completing a spell. In the particular case of bank failure, completing a spell is associated with the moment in which a bank is liquidated.

In the case of specifications which model the baseline hazard explicitly by making use of a particular parametric model, estimation can be done by the method of maximum likelihood. When the baseline hazard is not explicitly modeled, the conventional estimation method is partial likelihood estimation, developed by Cox (1972). The key point of the method is the observation that the ratio of the hazards (6) for any two individuals i and j depends on the covariates, but does not depend on duration:

$$\frac{\lambda(t, X_i, \beta, \lambda_0)}{\lambda(t, X_j, \beta, \lambda_0)} = \frac{\exp(X_i{}'\beta)}{\exp(X_j{}'\beta)} \qquad (8)$$

Suppose there are n observations and there is no censoring. If there are no ties, durations can be ordered from the shortest to the longest, $t_1 < t_2 < \cdots < t_n$. Note that the index denotes both the observation and the moment of time in which the duration for that particular observation ends. The contribution to the partial likelihood function of any observation j is given by:

$$\frac{\exp(X_j{}'\beta)}{\sum_{i=j}^{n} \exp(X_i{}'\beta)} \qquad (9)$$

the ratio of the hazard of the individual whose spell ended at duration t_j to the sum of the hazards of the individual whose spells were still in progress at the instant before t_j. The log-likelihood can then be written as:

$$\ell(\beta) = \sum_{j=1}^{n} \left[X_j{}'\beta - log \sum_{i=j}^{n} \exp(X_i{}'\beta) \right] \qquad (10)$$

Maximizing equation (10) with respect to β, estimators of the unknown parameter values are obtained. The intuition behind partial likelihood estimation is that without knowing the baseline hazard only the order of durations provides information about the unknown coefficients.

When there is censoring, the censored spells will contribute to the log-likelihood function by entering only in the denominator of the uncensored observations. Censored observations will not enter the numerator of the log-likelihood function at all.

Ties in durations can be handled by several different methods. In this paper, ties are handled by applying the Breslow method. In continuous time ties are not expected. Nevertheless, given that the moment of failure in practical applications is aggregated into groups (here months), ties are possible, and in fact they occur. Suppose we have three individuals labeled a_1, a_2, a_3 in the risk pool and in a certain moment, and a_1, a_2 fail. The Breslow method says that, given it is unknown which of the failures preceded the other, the largest risk pool will be used for both failures. In other words, this method assumes that a_1 failed from the risk pool a_1, a_2, a_3, and a_2 also failed from the same risk pool. The Breslow method is an approximation of the exact marginal likelihood, and is used when there are not many ties at a given point in time.

The model was estimated using the partial likelihood method. Results are presented in Table 1, which shows the values of the estimated coefficients and their standard errors. We present eight different specifications of the empirical model. Each specification includes a different subset of the covariates mentioned in the data section. One first important conclusion from Table 1 is that the null hypothesis that none of the indicators included in the model is important in explaining the behavior of duration is clearly rejected in all eight specifications. This provides evidence that supports the idea that failure of financial institutions during the period of financial distress can be explained by differences in financial health and prudence existing across institutions.

Regarding the role played by individual indicators, it can be seen that under all eight specifications cumulative abnormal loan growth affects positively and significantly the probability of failing. Results shown in Table 1 use an average of four years for the variable abnormal loan growth. It is noteworthy to mention that results are qualitatively identical when we used alternative averages of one year, two years and three years. Significance is lost when considering only point abnormal loan data as of June 1998. This result indicates that is sustained abnormal loan growth that matters for the probability of bank failure. The value of the coefficient is near 0.01 in the different specifications, indicating that a one percentage increase in the average four-year abnormal credit growth leads to a one percent increase in the probability of failing.

Not surprisingly, increases in the capitalization ratio and declines in non-performing loans lead to significant reductions in the hazard of failing in all cases. Poorly capitalized banks and banks with a highly deteriorated loan portfolio are more likely to fail than otherwise identical financial institutions. The other included variables report intuitive signs for their estimated coefficients, but are not always statistically different from zero at standard significance levels.

4.2 Cross-sectional time-series analysis

In this section we test the effect of abnormal loan growth on banks' financial health (solvency, non-performing loans and profitability), using quarterly cross-sectional time-series data between 1990 and 2011. The number of cross-sectional units is relatively small while the number of time periods is relatively large. More importantly, it is expected that the time dimension of the panel grows faster than the cross-sectional dimension. In this context, and contrary to traditional panel data settings, it appears reasonable to specify a common conditional mean function across the units, with heterogeneity taking the form of different variances rather than shifts in the means. The asymptotic theory here is with respect to time going to infinity, while the number of cross-sectional units is fixed.

Correlations across financial institutions are also very relevant in our dataset, as these institutions have established relations in different financial markets (e.g., money markets). Summing-up, rather than using traditional panel data techniques, such as fixed effects, random effects or dynamic panel data models, for our quarterly data sample we estimate a cross-sectional time-series model by Feasible Generalized Least Squares (FGLS), and estimate the structure of the variance-covariance matrix of the error terms.

Our empirical model is specified as follows:

$$y_{it} = \alpha + \sum_{s=1}^{8} \beta_s ALG_{i,t-s} + \gamma LEV_{\ i,t-1} + \phi PROV_{i,t-1}$$

$$+ \upsilon (SIZE \times ALG)_{it} + \delta BANK_{it} + \varepsilon_{it} \qquad (11)$$

where y_{it} represents the dependent variable, which depending on the specification may be the capital ratio of institution i at time t, the ratio of non-performing loans to total loans of institution i at time t, or profitability of bank i at time t.

The variance–covariance matrix of the error terms is specified to account for heteroskedasticity across panels (the variance of each panel differs), and to account for autocorrelation of order one specific to each panel.

Our main interest relies in estimating the sign and magnitude of β, standing for the long-run effect of abnormal credit growth on the dependent variable. This coefficient is estimated as the sum of the $\beta_s{}'s$ and its variance is estimated using the delta-method.

Table 2 presents a summary of our main findings and results, when using non-performing loans as the dependent variable. The variables included as regressors are jointly significant in explaining deviations of NPL_{it} around its mean, as indicated by the Wald-statistic. Every individual financial variable included in the regression is significant at the 1% level. Our main finding is that sustained increases in abnormal loan growth lead to significant increases in the ratio of non-performing loans to total loans. Particularly, a one percentage point upsurge in the two-year abnormal loan growth leads to a 1.6 percentage point increase in the ratio of non-performing loans.

This result supports the hypothesis that when banks' lending increases during a long period of time, an important portion of new loans are extended to clients without credit history or that under normal circumstances would have been rejected. Therefore, banks which present sustained periods of abnormal loan growth frequently take higher risks, and eventually present loan-portfolio deterioration. It is noteworthy noting that the effect of abnormal loan growth on non-performing loans differs according to bank size. Particularly, larger banks tend to experience a lower loan-portfolio weakening than smaller banks. The signs of all other included variables are as expected.

Table 2: FGLS estimation using quarterly data 1990:2 – 2011:1. Dependent variable is NPL_{it}

NPL_{it}	Coefficient	Standard Error
$LONG\ RUN\ ALG_{it}$	0.01555 ***	0.00306
$(SIZE \times ALG)_{it}$	-0.00002 ***	0.00001
$BANK_{it}$	-0.71296 ***	0.15757
LEV_{it-1}	-0.05747 ***	0.01233
$PROV_{i,t-1}$	0.01449 ***	0.00186
$CONSTANT$	0.03151 ***	0.00262
$Wald\ \chi^2_{(20)}$	6172.840	
$Prob > \chi^2$	0.000	

Table 3 shows results of estimating equation 11 using solvency as the dependent variable. As expected, abnormal credit growth excerpts a significant negative influence over banks' solvency in the long-run. This result shows that, on average, banks do not increase their capital buffers accordingly to the additional risk they are undertaking when credit significant expansions occur. In line with García-Suaza et al (2012), larger banks present a further reduction of capital buffers when incurring in abnormal loan growth for a long period of time.

Table 3: FGLS estimation using quarterly data 1990:2 – 2011:1. Dependent variable is CAP_{it}

CAP_{it}	Coefficient	Standard Error
$LONG\ RUN\ ALG_{it}$	-0.00773 ***	0.0029265
$(SIZE \times ALG)_{it}$	-0.00001 *	0.0000053
$BANK_{it}$	1.77713 ***	0.1490219
LEV_{it-1}	0.38360 ***	0.0117778
$PROV_{it-1}$	0.09790 ***	0.0160990
$CONSTANT$	5.93266 ***	0.2255836
$Wald\ \chi^2_{(20)}$	2621.080	
$Prob > \chi^2$	0.000	

Table 4 shows estimation results when using ROA_{it} as the explained variable. A very interesting result is observed. Note that although abnormal credit growth may have a positive impact on short-run profitability, in the long-run the effect is null. Hence, this result, together with those obtained when using solvency and the ratio of non-performing loans as explained variables, supports the hypothesis of banks' short-sightedness. In other words, when banks expand significantly their balance sheets, seeking for higher immediate returns or for larger market shares, they do not hedge appropriately against the higher risks in which they incur.

Table 4: FGLS estimation using quarterly data 1990:2 – 2011:1. Dependent variable is $\boldsymbol{ROA_{it}}$

$\boldsymbol{ROA_{it}}$	**Coefficient**	**Standard Error**
$\boldsymbol{LONG\ RUN\ ALG_{it}}$	-0.00002	0.0000359
$(\boldsymbol{SIZE} \times \boldsymbol{ALG})_{\boldsymbol{it}}$	0.00000	0.0000000
$\boldsymbol{BANK_{it}}$	0.01077 *	0.0056214
$\boldsymbol{LEV_{it-1}}$	0.00201 ***	0.0001131
$\boldsymbol{PROV_{it-1}}$	-0.00131 ***	0.0001594
$\boldsymbol{CONSTANT}$	-0.01576 **	0.0060882
$\boldsymbol{Wald\ \chi^2_{(20)}}$	380.290	
$\boldsymbol{Prob > \chi^2}$	0.000	

Prudential policies may need to be implemented. One alternative may be the imposition of individual additional capital charges to assure banks internalize the potential costs of their riskier behavior while balance-sheets expand. Another alternative may be the imposition of levies on the origination of new credit in the presence of abnormal loan growth. For instance, on March 2013 Peru implemented an individual marginal reserve requirement based on credit growth.

5. Concluding remarks

This study provides new evidence on the relationship between abnormal loan growth and banks' risk-taking behavior, using data from a rich panel of Colombian financial institutions.

We perform two different empirical exercises. On the one hand, we test the incidence of abnormal loan growth on banks' survival probability using information on individual banks' characteristics during the financial crisis of the late 1990s. On the other hand, we test the effect of abnormal loan growth on banks' financial health, using cross-sectional time-series data on Colombian financial institutions between 1990 and 2011.

Our main findings support the hypothesis of banks' inter-temporal short-sightedness. We show that abnormal loan growth during a sustained period lead to reductions in banks' capital ratios and to increases in the ratio of non-performing loans to total loans. Although abnormal credit growth may have a positive impact on short-run profitability, in the long-run the effect is null. Significant credit expansions do not generate corresponding increases neither in banks' safety margins nor in long-run profitability.

Concordant with these results, we also show that during the Colombian financial crisis of the late 1990s, sustained abnormal loan growth was one of the most significant variables in explaining observed differences in the process of bank failure.

These findings suggest that additional regulatory measures should be undertaken in order to assure financial soundness when abnormal loan growth is observed. One alternative may be the imposition of individual additional capital requirements to assure banks internalize the potential costs of their riskier behavior while balance-sheets expand. Another alternative may be the imposition of levies on the origination of new credit in the presence of individual abnormal loan growth.

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Table 1: Cox Proportional Hazards Model

Variable	Model (1)		Model (2)		Model (3)		Model (4)		Model (5)		Model (6)		Model (7)		Model (8)	
ALG_i^{48}	0.008 (0.004)	**	0.013 (0.005)	***	0.009 (0.004)	**	0.008 (0.004)	**	0.014 (0.005)	***	0.008 (0.004)	**	0.014 (0.005)	***	0.014 (0.005)	***
CAP_i	-0.079 (0.042)	*	-0.144 (0.051)	***	-0.072 (0.042)	*	-0.125 (0.048)	***	-0.149 (0.053)	***	-0.122 (0.052)	**	-0.202 (0.063)	***	-0.201 (0.066)	***
$SIZE_i$	-0.005 (0.003)	*	-0.007 (0.003)	**	-0.005 (0.003)		-0.005 (0.003)		-0.006 (0.003)	*	-0.005 (0.003)		-0.009 (0.004)	**	-0.009 (0.005)	*
$PROF_i$					-0.303 (0.189)				-0.321 (0.179)	*	-0.040 (0.248)				-0.013 (0.261)	
NPL_i			0.055 (0.024)	**					0.064 (0.027)	**			0.062 (0.029)	**	0.062 (0.029)	**
$COMP_i$							-0.054 (0.023)	**			-0.050 (0.033)		-0.051 (0.021)	**	-0.050 (0.034)	
$BANK_i$	-1.340 (0.739)	*	-2.030 (1.001)	**	-0.587 (0.858)		-1.239 (0.792)		-1.550 (1.072)		-1.142 (0.992)		-2.222 (1.072)	**	-2.199 (1.165)	*
$Log-likelihood$	-34.954		-32.642		-33.801		-32.642		-27.335		-32.629		-26.150		-26.149	
$Prob > \chi^2$	0.003		0.001		0.002		0.001		0.001		0.002		0.000		0.000	

Note: *, ** and *** denote significance at the 10, 5 and 1% level, respectively. Standard reported errors in parenthesis.