Use of Micro-data at the loan-to-loan level for the Design of Macropudential Policies

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Outline

Motivation

- Indicators such as NPL are frequently used to measure credit risk
- However, these are ex post indicators of the situation in the banking system
- In this sense, the ratio of action for the authorities is limited
- There is a need to have access to ex ante indicators that allow to take preventive actions.
- This could be possible by means of the use of micro-data.

A different dimension of the monetary transmission mechanism: the risk-taking channel

- The recent credit crisis has drawn the attention of researchers and policymakers to a different dimension of the monetary transmission mechanism the so-called risk-taking channel (Borio and Zhu, 2008)
- When interest rates are below historical levels for a long period of time, the monetary policy may cause a moderation in perceived risk contributing to the build up a crisis.
- In times when interest rates are too low, the search for yield is often associated with the expansion of investment into riskier assets and borrowers as downside risk are played down. Adrian and Shin (2008).

Risk taking: ex post vs ex ante indicators

- The most common risk indicators are ex post risk indicators such as NPL.
- This indicators are not good to analyze the build up of financial crises.
- Usually when the loan growth is above average, NPL are low
- While the opposite happens when a crisis strikes.
- High NPL are the materialization of the risk that banks took some periods before.
- Ex ante credit risk indicators are necessary to assess the risk taking behavior of banks.

Credit risk and ex ante indicators

- The risk taking behavior of banks is a medium term concept.
- At the origination of the loan (new loan) the probability of default is high because the supply of loans is to risky borrowers.
- But in that moment the bulk of the loan portfolio has been granted to safer borrowers.
- In the medium term, the size of the loans granted to riskier borrowers is higher relative to the loans granted to safer borrowers.
- Therefore it is important to identify this ratio.

Credit risk and ex ante indicators

- Two approximations:
  - First an ex-ante borrower level proxy: Probit models: whether a loan is granted to a borrower with bad credit history or no credit history.
  - But this not imply risk-taking per se because the net-worth of the risky borrowers also improve when interest rates are low.
  - Second: duration models that allow us to analyze the impact on loan default probability of interest rates during the life of the loan:
    - At origination: new loans
    - For outstanding loans.

The credit risk measures and the data

- The basis for the estimation of a measure of bank risk is a data set for Colombia, consisting of quarterly information on 2,095,755 individual commercial loans for the period 2000:I to 2008:IV provided by Superfinanciera, and a sample of 131,265 (13% of population) consumer loans (different to credit card and automobiles) for the period 2000:I to 2011:II.

Form 341

SUPERINTENDENCIA BANCARIA OF COLOMBIA
INDIVIDUAL REPORT BY BORROWER
FORM 341

Entity: _____ (Type) _____ (code) _____ (Name)

Borrower: _____ (Type) _____ (Identification) _____ (Check) _____ (Name) _____ (Ciu)

Date: _____ (DD/MM/YYYY)

Subaccount	Concept	1	2	3	4	5	6	7	8	9	10	11	12
		#. of operations		Principal		Interest		Other concepts		Interest Contingencies		Provisions	
		L/C	F/C	L/C	F/C	L/C	F/C	L/C	F/C	L/C	F/C	L/C	F/C
010	Commercial A												
020	Commercial B												
030	Commercial C												
040	Commercial D												
050	Commercial E												

Form 341

13	14	15	16	17	18	19	20	21	22	23	24	25	26
Warranty				Expected Instalment				Actual Instalment				Redescount	Initial date of the loan
				Principal		Interest		Principal		Interest			
L/C	F/C	Tipo	F. último avaluo	L/C	F/C	L/C	F/C	L/C	F/C	L/C	F/C		

Form 341

27	28	29	30	31	32	33	34	35	36	37	38	39	40
Due date of the loan	Initial rate of the loan	Days in dealy	SARC										
			Model	Probability of default	Individual provisions				Exposure		Discount rate		Loss given default
					L/C	F/C	L/C	F/C	L/C	F/C	L/C	F/C	

Information

- We were able to obtain information for:
  - Borrower (age as borrower, borrower risk, number of bank relationships),
  - Loans (amount, collateral, maturity and payment information)
  - Provisions
  - Bank (bank size, leverage, NPL): Banks' balance sheets

The monetary policy stance

- In principle, there could be a two-way relation between loan risk and monetary policy.
- We used as the stance of monetary policy the deviations of the policy rate from the natural rate of interest (as in Gambacorta (2009)).

The probit model

- Relationship between short term interest rates at origination and loans to borrowers with
  - Risky Borrower: Recent bad credit history (RBCH) or no credit history (NCH)
  - RBCH: a borrower that was in default in the six previous months the date he/she obtained a loan.

The duration model

- Duration: We use a duration or hazard function model to study the time to default of individual bank loans.
- In duration models the dependent variable is duration, in this case, the time it takes for a loan to change from one state to another.
- Let T represent the time that elapses before the occurrence of the default of the loan. The passage of time is often referred as a spell.
- A simple way to describe the behavior of a spell is through its survivor function,$S(\xi) = P(T \geq \xi)$, which yields the probability that the spell T lasts at least to time ξ
- Alternatively, the hazard function determines the conditional probability that the spell ends in a short time after.

Probit model: commercial loans

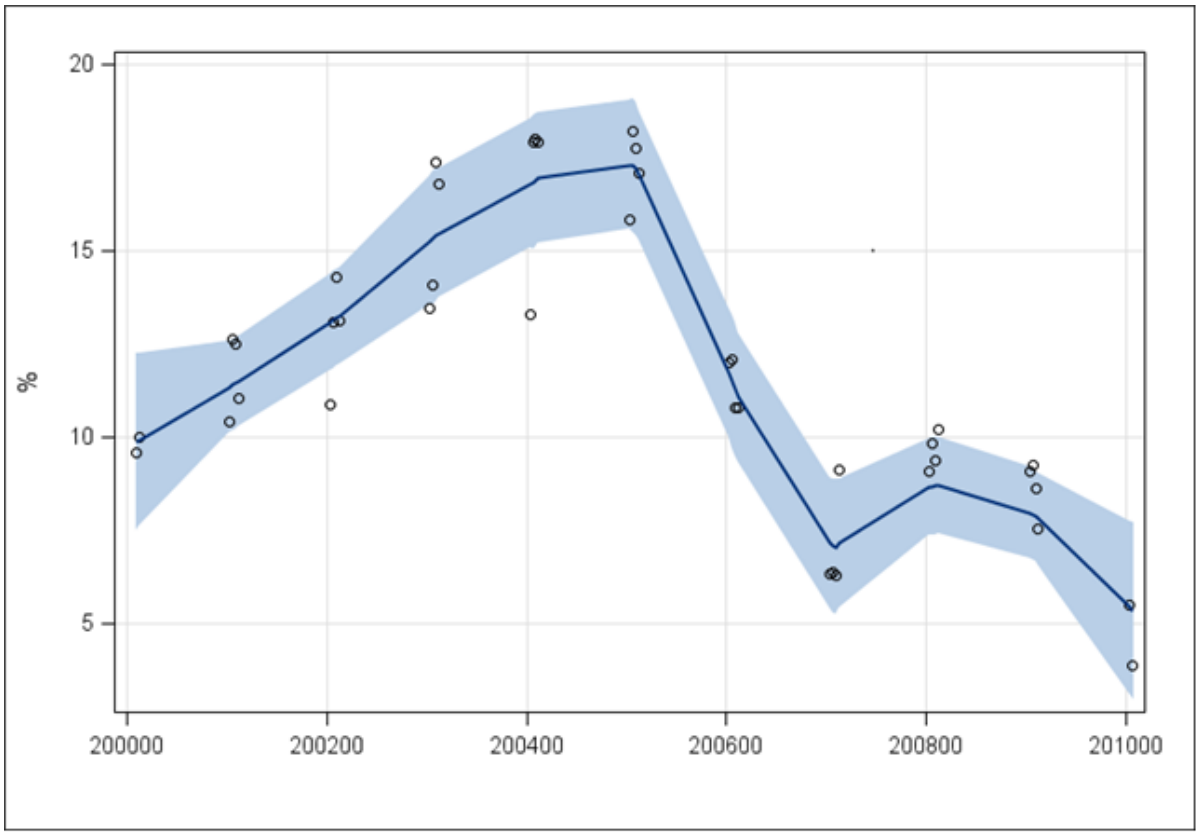
Independent variables	Recent Bad Credit History	No Credit History
INTEREST RATE$_{\tau-1}$	-0.01	-0.15
BANK SIZE $_{b\tau-1}$	-0.02	0.03
OWN FUNDS/TOTAL ASSETS$_{b\tau-1}$	-0.02	0.12
INTERBANK P /TOTAL ASSETS$_{b\tau-1}$	0.00	-0.05
BANK NPL$_{b\tau-1}$ - NPL$_{\tau-1}$	0.00	-0.01
LN (2+AGE AS BORROWER$_{fl\tau}$)	-0.36	1.61
LN (2+NUMBER OF BANK RELATIONSHIPS$_{fl\tau}$)	-0.98	1.44
LN (SIZE OF THE LOAN$_{l\tau}$)	-0.01	0.01
COLLATERAL $_l$ (0/1)	0.04	-0.04
MATURITY $_l$ 0m.-3m.(0/1)	0.10	0.37
MATURITY $_l$ 3m.-1y. (0/1)	-0.05	-0.02
MATURITY $_l$ 1y.-3y.(0/1)	0.11	0.03
GPDG$_{\tau-1}$	-3.50	-13.75
FINANCIAL INCOME/ATA$_{l\tau}$	0.23	-0.25
EFFICIENCY RATIO$_{l\tau}$	-0.03	-0.48
TIME TREND	-0.01	0.09
TIME TREND^2	0.00	0.00
CONSTANT	3.18	-4.81
No. of Observations (Loans)	738.782	234.364
(-2)Log pseudolikelihood	527.68	923.13
χ^2 (p-value)	0.001	0.001

Non Time-Varying Duration Models: commercial loans

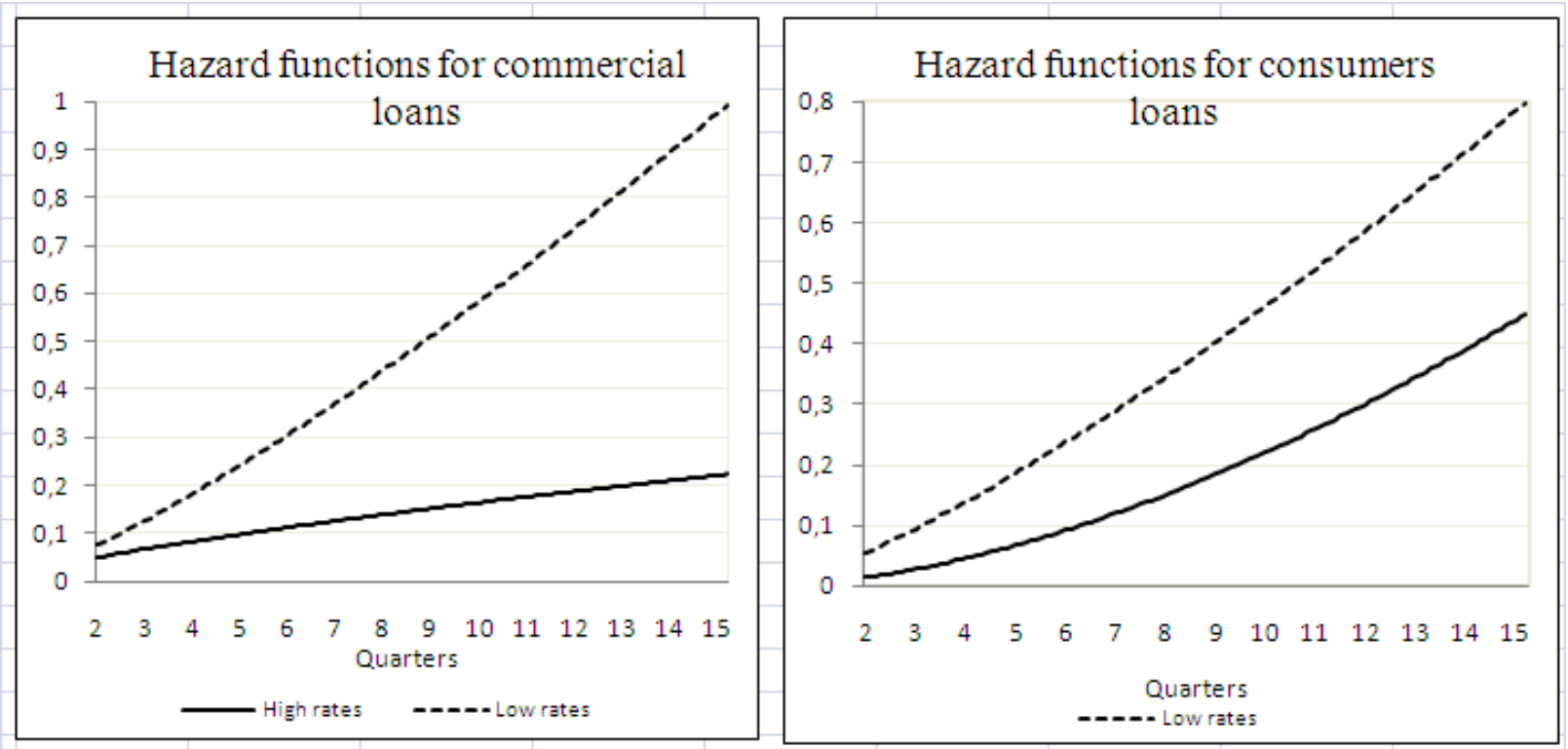
Independent Variables	Weibull	Weibull with interaction	Weibull with interaction
INTEREST RATE$_{t-1}$	-0.0045***		
INTEREST RATE$_{t+T-1}$	0.1754***		
INTEREST RATE$_{t-1}$ * BANK SIZE$_{b,t-1}$		0.0036***	
INTEREST RATE$_{t-1}$* OWN FUNDS$_{b,t-1}$			0.0006***
BANK SIZE$_{b,t-1}$	-0.0237***	-0.0308***	-0.0235***
OWN FUNDS/TOTAL ASSETS$_{b,t-1}$	-0.0226***	-0.0225***	-0.0252***
INTERBANK POSITION /TOTAL ASSETS$_{b,t-1}$	0.0192***	0.0200***	0.0199***
BANK NPL$_{b,t-1}$- NPL$_{t-1}$	0.0056***	0.0053***	0.0054***
BORROWER RISK$_{t-1}$ (0/1)	0.0005***	0.0005***	0.0005***
LN (2+AGE AS BORROWER$_{t-1}$	0.0409***	0.0383***	0.0373***
LN (SIZE OF THE LOAN$_{l,t-1}$	-0.0112***	-0.0109***	-0.0114***
COLLATERAL$_l$ (0/1)	0.3422***	0.3440***	0.3429***
MATURITY$_l$ 0m.-3m. (0/1)	-1.0141***	-1.0083***	-1.0102***
MATURITY$_l$ 3m.-1y. (0/1)	-0.3214***	-0.3237***	-0.3252***
MATURITY$_l$ 1y.-3y. (0/1)	0.0211***	0.0263***	0.0251***
GPDG$_{t-1}$	0.8327***	0.9013***	0.9446***
GPDG$_{t-T-1}$	-9.4598***	-12.6153***	-12.5946***
TIME TREND	-0.0061***	-0.0059***	-0.0058***
TIME TREND 2	-0.0003***	-0.0002***	-0.0002***
CONSTANT	2.7283***	2.6832***	2.6491***
ln(α) (duration dependence)	0.5696	0.5703	0.5703
Log pseudolikehood	-609386	-609144	-609379

An ex ante risk taking indicators: The supply of loans to risky borrowers

- Consumer Loans: Ratio of loan amount to Risky/Safe Borrowers

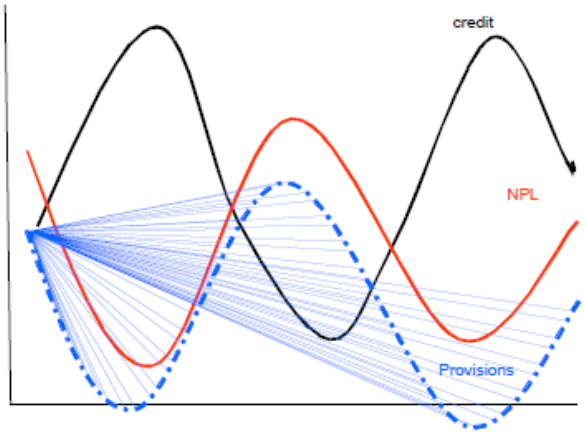


An ex ante risk taking indicators: Hazard Function. Comparison between commercial and consumer loans



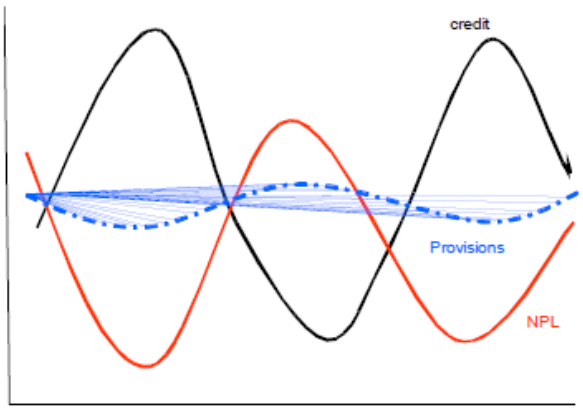
Dynamic Provisioning: The Theory

Normal provisioning



- Provisions depend on contemporary NPLs
- In the upturn: GDP and credit grow above potential, so does credit. Collateral prices rise. Low NPLs, low provisions
- In the downturn, the opposite

Dynamic provisioning



- Goal: to smooth provisions along the cycle and avoid procyclicality
- Aim: try to obtain a flat provisioning effort in terms of the ratio of provisions to credit

Source BBVA.

Countercyclical Loan Provisions in Colombia

- As pointed out by Jimenez et. al (2012):
  "Among macroprudential instruments, the ones that have attracted most interest are countercyclical tools".
- Concerned about financial stability issues, the Superfinanciera introduced a countercyclical component to the individual provisions since July 2007.
- This component corresponds to the part of individual provision that is accrued in an additional form for each borrower during good times.
- The regulator, using historical data calculates two risk scenarios, A and B (B is the riskier scenario)
- The output of this calculations are two default probability matrices which contain default probabilities for every type of credit and borrower.

Countercyclical Loan Provisions in Colombia

- Provisions, based on expected losses: $P = OVL * PD * LGD$
- The countercyclical provisioning system is a rule based system
- Each financial institution must accumulate or deplete its countercyclical provisions according to four criteria:
  - Deterioration of portfolio: $\Delta Provisions \geq 9\%$
  - Efficiency: $(PNR/IxI) \geq 17\%$
  - Fragility: $0 \leq PNR/GFM) \geq 42\%$
  - Loan growth: $\Delta CB < 23\%$

Countercyclical Loan Provisions in Colombia

- Default situation: if any of the four indicators is not met, the entity will be subject to accumulation of anticyclical provisions (upturn).
- If the four indicators are met 3 consecutive months, the entity will enter the depletion phase (downturn).

Counterfactual model

- Our goal in this section is to assess the causal effect of countercyclical provisions by means of a counterfactual model.
- In this model, we use the set of characteristics of the loans that were granted after the intervention, July 2007, and use them to obtain a set of loans granted before the intervention with "exactly" the same characteristics.

The propensity score

- This is done by computing a propensity score for each loan.
- A propensity score is a probability value that provides information about the likelihood that an unit has received treatment given a set of covariates
- The covariates used are bank characteristics, loan characteristics, borrower characteristics and macroeconomic conditions.
- This conditional probability is predicted by a probit model.

The propensity score

- In a random database, for the period 2003.1-2011.2, the propensity score will give us the probability
  - that a loan will be assigned to a control group (group without countercyclical provisions)
  - or to a treatment group (group with countercyclical provisions).
- Then, using the propensity score, we match the loans in the control group with those in the treatment group.
- The resulting matched credits make up a set that reflects a synthetic situation in which there is a loan market of exactly the same characteristics before and after 2007.

Causal effect

- At this stage, we are able to assess the causal effect of the countercyclical provisions on loan growth using as econometric specification the equation:

$$LLoanA_{q,l,t} = \alpha + \beta * Treatment + Treatment * Characteristics_{q,l,t} + e_{q,l,t} \quad (2)$$

$LLoanA_{q,l,t}$ is the natural log of the amount of the loan in the q-percentile; *Treat* indicates if the credit was granted during the period 2007.3 and 2011.2; $Characteristics_{q,l,t}$: bank characteristics and $e_{q,l,t}$ is the error term.

Results on effectiveness

Table : Countercyclical provisions effect on the amount of the loans: Counterfactual distribution

Without interaction

Effect	q_5 **Coeff.**	q_{10} **Coeff.**	q_{25} **Coeff.**	q_{50} **Coeff.**	q_{75} **Coeff.**	q_{90} **Coeff.**	q_{95} **Coeff.**
Dependent variable:	$LLoanA_{q,l,t}$						
TREATMENT	-10.91 ***	-9.45 ***	-6.96 ***	-6.25 ***	-6.22 ***	-6.93 ***	-8.18 ***
CONSTANT	14.72 ***	15.62 ***	16.95 ***	18.13 ***	19.37 ***	20.93 ***	22.18 ***

An ex ante dimension for the dynamic provisions system in Colombia

- The dynamic provisions in Colombia use ex post information to compute the PD in the matrices A and B.
- One way to use ex ante information is to combine the information provided in real time by the indicator of loan amount of risky/safe borrowers with the beliefs of the experts that computed the PD in the matrixes A and B.
- The result would be an updated PD for good and bad times with ex ante information that would be used for the calculations of the provisions.

Summary

- Using micro-data of the lending portfolio in Colombia it is possible to assess:
  - The relevance of the use of ex ante information to analyze the risk taking behaviour of banks.
  - It is possible to measure the effectiveness of some macroprudential policies in the banking sector
  - It is posible to implement indicators that:
    - Measure in real time risk taking behavior of the banking system
    - Measure the response of the PD of different types of loans to different levels of policy interest rates
    - Could anticipate ex ante credit risk and
    - To improve the actual provisioning system in Colombia to take into account real time risk taking behaviour.