Loan loss provisions in the mortgage market: a quasi-natural experiment

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This paper (1/3)

In January 2016 the Chilean banking regulator raised **provisioning** for losses related to mortgage loans (for **ex-post** delinquent borrowers with high leverage)

- Research question
  - Did this regulation affect the mortgage loan market?
  - If so, how exactly?
- We argue that
  - The new regulation did affect the supply of mortgage credit
  - The regulation makes *ex-post* delinquent borrowers more costly, and if possible banks would like to avoid them *ex-ante*
  - We argue that LTV is an informative signal, which together with the specifications of the regulation, resulted in an *endogenous* LTV limit
  - Such LTV limit is indeed a contraction of the credit supply

This paper (2/3)

- We elaborate our argument in two parts

  1.- Adapt a small off-the-shelve screening model under imperfect information.
  - Analyze extensions to the model to assess alternative hypothesis

  2.- With a quantitative exploration of said model, we guide our empirical examination. We use
  - A matching approach
  - Administrative micro data from Internal Revenue Service (IRS) and the Cadastre of Non-farming Real Estate Properties
  - Census data of all real estate transactions from 2002 to date

This paper (3/3)

- Our findings are

  i) Fewer and smaller loans were granted: On average the mean borrower had to raise extra funds for down-payment equivalent 3% of property value
  ii) The regulation design implies that for a wide set of other model parameters, LTV ratios would collapse at 80%
  iii) The empirical examination shows exactly that
  iv) A separating equilibrium through interest rates is not an equilibrium outcome

Where do we fit in the literature? (1/1)

- Growing literature on the evaluation of effectiveness of macro-prudential policies
  - General cross country evidence: IMF(2011); Crowe et al. (2013); Hott (2015)
- For the housing market in particular,
  - Cerutti et al (2017) dissects the cross country evidence on house prices and mortgage credit. Housing booms are more likely in countries with high LTV ratios
  - Kuttner and Shim (2016) stress that LTV and DTI together work better for taming housing booms (complementarity)
- Macro-prudential evaluation and micro-data literature is thinner
  - Beltratti (2017) evaluate the effects of the elimination of pre-payment penalty of mortgage loans with administrative Italian data.

Background: The New Regulation (1/4)

- Specifics of the regulation issued by the Chilean banking supervisor
  - In Dec. 2014 it announced a new regulation that increased mortgage loan loss provisions starting January 2016
  - Before 2016, every commercial bank decided on their provisioning levels, but it was the view of the regulator, that these were insufficient
  - Specifics
    a) **Complementarity**: Provision contingent on ex-post delinquency and loan-to-value at the moment of nonperformance
    b) **Timing**: Once a month provisions are recalculated
    c) **Which loans**: All mortgage loans are subject to it.
    d) **Size**: Can go as high as 30% of loan

Background: The New Regulation (2/4)

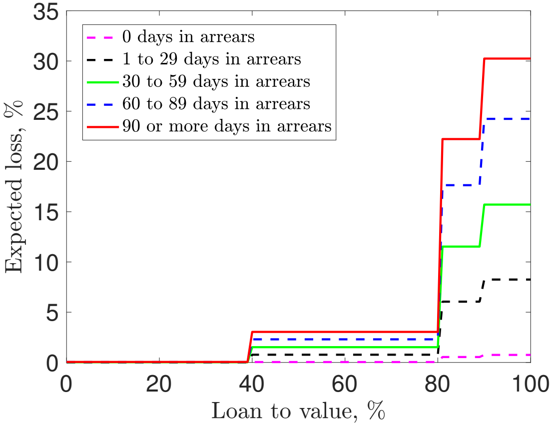


Figure: Financial provisions under new regulation: Expected loss (vertical axis, in percentage), according to Loan to Value ratio (horizontal axis), and days in arrears at the end of the month. Source: SBIF Chaper B-1 in "Compendio de Normas Contables"

Background: A Glance of Motivation (3/4)

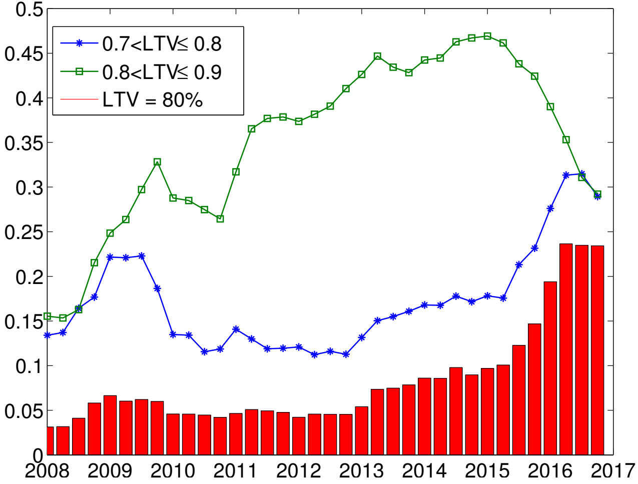


Figure: Fraction of mortgage loans with different loan-to-value ratios: Vertical axis is loan-to-value, data is quarterly and each observation is the fraction of loans on quarter granted loans

Background: The Data (4/4)

- The IRS collects data at the moment any real estate transaction takes place (known as Form 2890)
- F-2890 includes data on
  - Price of the property
  - Name of the lender financial institution
  - Cash downpayment
  - Flag for natural person or company
  - ID of buyer
- Real Estate Property Cadastre
  - Flag for residential property
  - Flag house / apartment / parking lot / storage facility
  - Address

Model (1/6): A Simple Model of Financial Screening

- Why a model?
  - The regulation has many things happening at once. A model helps us understand the role of each piece
  - Guides our empirical examination
  - Allows us to understand why certain hypothesis would not be equilibrium outcomes and under what assumptions
- Benchmark model and alternative setups

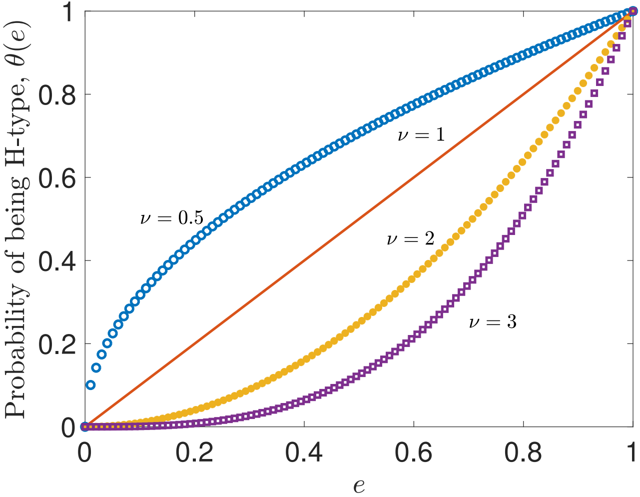
Model (2/6): Borrowers' heterogeneity

- Continuum of new borrowers shows up at the bank to ask for a loan to buy a house. Index them with $e \in [0, 1]$ which they observe
  - H-type borrowers never enter into arrears,
  - L-type borrowers do so with constant probability $\delta > 0$
- Unobservable idiosyncratic probability of being a (high) H-type borrower:

$$\theta(e) = e^{\nu}$$

- ν measures the scarcity of H-type borrowers
- Then, e is the idiosyncratic quality ranking of borrowers
  - Cannot credibly/accurately communicate their quality ranking
  - Only up to a signal $\tilde{e} \propto e$

Model (2/6): Borrowers' heterogeneity



Model (3/6): Value of lending to H/L-types: V^H, V^L

- Financial intermediary has alternative cost r, and lends at rate $\hat{r}$
- For simplicity we assume a perpetuity
- Value of lending to H-type borrowers

$$V^H(L_t) = (\hat{r} - r)\, L_t + \frac{1}{1+r} V^H(L_{t+1})$$

- Value of lending to L-type borrowers

$$V^L(L_t) = (\hat{r}_t - r_t - r_t \delta \psi) L_t + \frac{1}{1+r} V^L(L_{t+1})$$

  with ψL the associated provision

- Ex-ante both types of borrowers are indistinguishable. Borrower knows his e, but learns his type (H/L) only **after** loan is granted

Model (4/6): The Signal

- Unlike the US, credit score data is unavailable in Chile for banks.
- Banks use own credit risk analysis, and rely heavily on DSTI and LTV to allocate scarce funding
- We emphasize the informational role of the LTV ratio, but do not neglect there may be other informative signals. Let $\tilde{e} = 1 - LTV$
- Let $\tilde{e} \in [0, 1]$ stand for the noisy signal, which is positively correlated with e

$$\tilde{e} = \begin{cases} e & \text{with probability} \quad \rho \\ \sim U[0,1] & \text{with probability} \quad 1-\rho \end{cases} \tag{1}$$

where ρ is the bank's screening technology accuracy

Model (5/6): Problem of the financial intermediary

- We can express the loan size, and the value of lending in terms of the signal $\tilde{e}$;
  - $L = (1 - \tilde{e})P$
  - $V^j(L) = V^j(\tilde{e})$, $j = L, H$

- Given $\{r, \hat{r}, P, \delta, \psi\}$ the problem of the financial intermediary is to choose $\bar{e}$ to solve

$$\max_{\bar{e}_t} \int_0^1 \int_0^1 \mathbb{1}\{\tilde{e}_t \geq \bar{e}_t | e_t\} \Big[\theta(e_t) V^H(\tilde{e}_t) + (1 - \theta(e_t)) V^L(\tilde{e}_t)\Big] d\tilde{e}_t de_t$$

- The FOC is given by

$$\rho \bar{e}^{\nu} = 1 - \frac{1-\rho}{\nu+1} - \frac{\hat{r} - r}{r\delta\psi}$$

Model (6/6): Problem of the financial intermediary

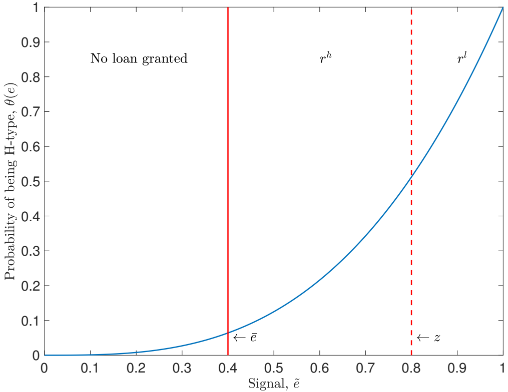
Proposition

A Loan to Value limit ($\bar{\ell} = 1 - \bar{e}$) is endogenously determined by the introduction of a provisioning cost for the contingent L-type borrower. This limit is

1. *Non-increasing in the expected cost of the provision, $\delta\psi$*
2. *Non-increasing in the scarcity of good borrowers, governed by parameter ν.*
3. *Non-decreasing in the net profitability of each granted loan, as captured by the spread $\hat{r} - r > 0$*

Extensions (1/6): Screening with two interest rate schedules

- Why not charge two interest rates based on the signal $\tilde{e}$?
- 3 intervals: Bank can deny credit, charge r^h, or $r^l < r^h$



Extensions (2/6): Screening with two interest rate schedules

- Given $\{r^h, r^l, r, P, \delta, \psi\}$ the problem of the financial intermediary is choosing $\{\bar{e}, z\}$ to solve

$$\max_{\{\bar{e},z\}} \int_0^1 \int_0^1 \mathbb{1}\{\tilde{e} \geq \bar{e}|e\} \Big[\mathbb{1}\{\tilde{e} < z|e\} [\theta(e) V^H(\tilde{e}, r^h) + (1-\theta(e)) V^L(\tilde{e}, r^h)] \\ + \mathbb{1}\{\tilde{e} \geq z|e\} [\theta(e) V^H(\tilde{e}, r^l) + (1-\theta(e)) V^L(\tilde{e}, r^l)] \Big] d\tilde{e}_t de_t$$

where the first order condition with respect to z boils down to

$$(r^h - r - r\delta\psi)(1-z) - (r^l - r - r\delta\psi)(z-1) = 0$$
$$z = 1$$

- To the right of $\bar{e}$ (same as benchmark) financial cost is paid anyhow. Why not charge r^h?

Extensions (3/6): Including competition

- Two interest rates, charged by different banks: low rate, r^l; and high rate r^h
- Conditional on r^k, $k = h, l$ banks choose $\bar{e}_j, j = 1, 2$
- Mass of borrowers is normalized to two for comparability
- Borrowers can go to any bank they want
  - If rates are the same, $r_1^k = r_2^k$; costumers randomize
  - If bank 1 deviates to $r^l = r^h - \epsilon$ then costumers no longer randomize and go to cheapest bank

Extensions (4/6): Including competition

- Problem with actions (r_1^l, r_2^h).
- **Bank 1:** The optimal cut-off rule for bank 1 solves benchmark problem, with twice more profits

$$\rho \bar{e}_1^{\nu} = 1 - \frac{1-\rho}{\nu+1} - \frac{r^l - r}{r\delta\psi}$$

- **Bank 2:** Fraction of borrowers with $\tilde{e} > \bar{e}_1$ already have loans
  - Problem: given $\{r^h, r, P, r_1^l, \bar{e}_1\}$ chose $\bar{e}_2$ to solve

$$\max_{\bar{e}_2} 2 \int_0^1 \int_0^{\bar{e}_1} \mathbb{1}\{\tilde{e} \geq \bar{e}_2 | e\} \Big[\theta(e)\Delta(\tilde{e}) + V^L(\tilde{e}, r^h)\Big] d\tilde{e} de$$

  - Notably, the FOC is unchanged

$$\rho \bar{e}_2^{\nu} = 1 - \frac{1-\rho}{\nu+1} - \frac{r^h - r}{r\delta\psi},$$

Extensions (5/6): Including competition

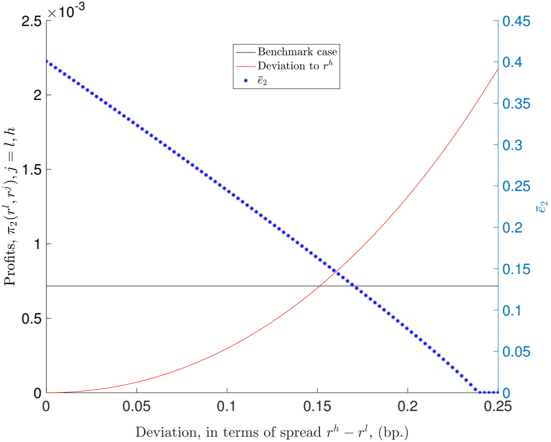


Figure: Profits and cut-off strategy for bank 2: Figure shows $\pi_2(r^l, r^l)$ in black, $\pi_2(r^l, r^h)$ in red, and the optimal cut-off rule as a function of $r^h - r^l$.

Extensions (6/6): Including competition

- Two areas. Small/Large $r^h - r^l$
- Small deviations with $r_2^h - r_1^l > 0$:
  - it is better to charge r_2^l
  - profits $\lim_{r_2^h \to r_1^l} \pi_2(r_1^l, r_2^h) \to 0$,
  - charging r_2^l results in $\pi_2(r_1^l, r_2^l) > 0$
- Large deviations with $r_2^h - r_1^l >> 0$:
  - nothing stops bank 1 to charge $r_1^l < {r_1^l}' = r_2^h - \epsilon$, with $\epsilon \to 0$
  - action by bank 1 moves us back to "small deviation case"
- Competition implies that a separating equilibrium cannot be sustained

Using the model (1/3): Simplifications

- Demand for mortgage loans is completely inelastic
- We have ruled out separating equilibrium but did not pose a GE model to determine exactly how much higher $\hat{r}$ would be
- No strategic interaction between borrowers and creditors: all bargaining power belongs to the financial institution
- Univariate signals; no role for previous payment behavior, lending relationships, other collateral, credit scoring
- Sill, we want to use model to understand how scarce credit was allocated through the LTV ratio

Using the model (2/3): Simplifications

Table: Baseline Calibration

Parameter	Value	Target	Source/Target
ρ	0.90		Ates and Saffie (3013)
r	3.5		Banco Central de Chile (2017)
$\hat{r}$	3.7	2.73% markup (1)	Banco Central de Chile (2017)
δ	0.29	9% (2)	Pacheco et al. (2014)
ν	0.69	90% LTV (3)	Median of LTV distribution, 2015

Notes: (1) markup is consistent with the CAR and ROE ratios reported in Chapter IV of Banco Central de Chile (2017); (2) Figure 2.1 in Pacheco et al. (2014), share of borrowers who are delinquent, non-value weighted. To match this moment it is also necessary to calculate the probability of being L-type, conditional on being granted a loan. That is, $\mathbb{E}[\theta(e)|e > \bar{e}] = \frac{1}{\nu+1}(1 - \bar{e}^{1+\nu})$; (3) endogenous LTV limit of 90% at $\psi = 12.5\%$.

Using the model (3/3): Introducing the non-linearity of the regulation → 80% LTV threshold is important

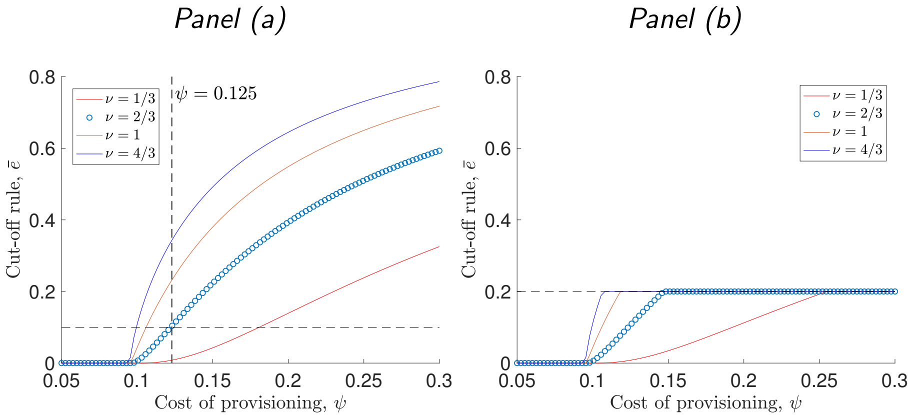


Figure: **Financial provision under new regulation**: Optimal threshold setting under of the simple model for different costs of financial provision, scarcity of good borrowers and non-linear regulation parameters.

Empirical part: A matching exercise (1/7)

- The goal of any matching method is to reduce **model dependence** $\rightarrow$ research discretion
- Matching methods
  - Contrasting outcomes of "programme" participants (Y_1) with "comparable" non-participants (Y_0)
  - If the groups are "comparable", then all difference in outcome is attributed to the program
- In particular, we use the Coarsened Exact Matching (CEM) method by Iacus, King and Porro (2012)
- The change in the regulation is an *exogenous* event to the buying decision of any given household. Also households cannot influence the regulation.

Empirical part: A matching exercise (2/7)

- As in Smith and Todd (2005) define a dummy $D = 1$ if property bought in 2016/17; and $D = 0$ if bought in 2012-2014.
- Object of interest is average treatment effect on treated

$$ATT = E(Y_1 - Y_0|D = 1, X) = \underbrace{E(Y_1|D = 1, X)}_{observed} - \underbrace{E(Y_0|D = 1, X)}_{unobserved}$$

  - $E(Y_0|D = 1, X)$ unobserved counterfactual that needs and approximation:

$$E(Y_0|D = 0, X)$$

  - Potential selection bias

$$B(X) = E(Y_0|D = 1, X) - E(Y_0|D = 0, X)$$

Empirical part: A matching exercise (3/7)

- Heckman (1998) stresses the fundamental identification condition: *conditional mean independence*

$$E(Y_0|D=1,X)=E(Y_0|D=0,X),$$

- We also require *Common Support Condition*

$$S=\mathsf{Supp}(X|D=1)\cap\mathsf{Supp}(X|D=0)$$

  - For every X, a control match can be found for treated and untreated groups
  - Limit control group to buyers before Dec. 2014 to limit selection bias

Empirical part: A matching exercise (4/7)

We use the CEM algorithm by Iacus, King and Porro (2015)

- Tries to approximate a fully blocked experiment
- Ideally we would want exact matching: trade-off between balance & producing matches
- In rough terms
  1. Coarsen the confounding variables (X) into meaningful groups
  2. Build $k-$dimensional strata
  3. Prune all strata with no matches of controls and treated obs.
  4. Drop the coarsening, calculate weights
  5. Then do any statistical test you need on balanced sample
- Note that CEM implies commons support by construction, no need to check later like with PSM

Empirical part: A matching exercise (5/7)

- Covariates are in vector $\mathbf{X}$, and if excluded can potentially generate imbalance
- Include: income (bracket); property price; comuna; lenght of mortgage loan; size of the real estate property; house/apartment
- Method works better if coarsening "makes sense". We use judgment for: loan length = 5 years; no further coarsening in comuna; income; house/apartment
- Imbalance is checked. Idea is that after pruning every treated observation has a control in the same strata to compare with.

Empirical part: A matching exercise (6/7)

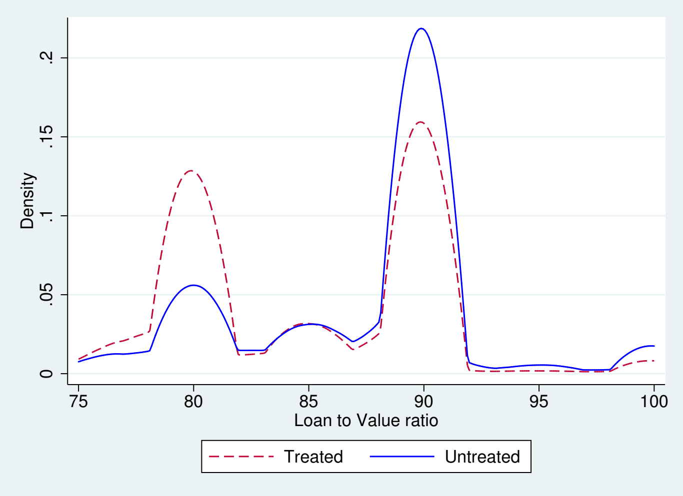


Figure: Balanced samples

Empirical part: A matching exercise (7/7)

Table: **Difference in means after matching:** Average Treatment on the Treated. Notes: *** significant at 1% level, t-stats in parenthesis.

Average Treatment Effects on Treated *Outcome variable: Loan To Value ratio*			
	ATT	ATT $\|LTV < 0.8$	ATT $\|LTV > 0.8$
Treated ($D = 1$)	-2.78***	2.11***	-1.23***
	(-32.03)	*(13.65)*	*(-35.55)*
Constant	82.17***	64.8***	89.1***
	(2269.16)	*(884.70)*	*(6813.23)*
Num. Obs	168640	49513	112473
R2	0.01	0.01	0.01

Percentiles in estimated CDFs around LTV=80%		
	$D = 0$	$D = 1$
Prob ($LTV \leqslant 79\%$)	0.239	0.291
Prob ($LTV \leqslant 79.9\%$)	0.268	0.361
Prob ($LTV \leqslant 80\%$)	0.309	0.461
Prob ($LTV \leqslant 80.1\%$)	0.313	0.473
Prob ($LTV \leqslant 81\%$)	0.348	0.536

Conclusions

- The goal of this paper was to assess the effects on the supply of credit of the new regulation on banking provisions for mortgage loans
- We build a model of imperfect information that results in an endogenous LTV cap, and used it to guide our empirical examination
- We look at a wide set of parameter families, and conclude that the design of the regulation implies bunching of borrowers at the 80% LTV limit
- Our empirical examination aims at reducing model dependence, using the matching estimator CEM. With a balanced sample we can
  - Calculate ATT to be 2.7% which takes mean borrower to just below 80% threshold
  - Different calculation not shown here, with same balanced sample implies that 6% of potential borrowers were ousted of the market