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Access and Risk: Friends or Foes?

Lessons from Chile

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Abstract

This paper documents the link between risk, stability, and access to credit markets in an emerging economy. Annual credit loss distributions of Chilean banks are presented for the period 1999-2005 providing, we believe, the first empirical evidence of the cyclical pattern of expected losses and unexpected losses of bank loan portfolios in emerging countries. The paper provides three main contributions to the debate on bank solvency and access to credit markets. First, it derives non parametric estimators of expected losses and unexpected losses, free from model error and, in particular, from distributional restrictions. Second, it shows how the distribution of credit losses for portfolios of retail and commercial loans is affected by the lumpiness of bank loans. Finally, it shows that the shape of credit loss distributions helps select appropriate policies to promote broader and sounder access to bank credit for the poor and the unbanked.

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I. INTRODUCTION

Risk-based capital requirements have often been identified in emerging countries with a higher cost of credit and more restricted access to bank lending. It is not surprising that strict adherence to risk management precepts and support for broader access to bank credit have often been perceived as antagonistic strategies. This paper supports the opposing view that risk management and access policies are, instead, complementary. From a conceptual viewpoint, it is clear that the improvement of credit risk assessment implies, for any given level of accepted bad borrowers (Type II error, assuming the null of solvency), a smaller number of rejected good borrowers (Type I error). Good risk assessment, if anything, should improve access to credit markets, moving forward the frontier of eligible bank customers by reducing the grey zone, where a blurred perception of risk impedes credit decisions.

The main subject of this paper is credit risk, and the tools under consideration are largely drawn from the literature on credit risk measurement. The conclusions, though, reach beyond the traditional area of bank solvency and shed new light on the conditions under which previously excluded individuals and communities could gain access to credit markets. In particular, we argue that loan loss distributions – a central component in any credit risk assessment – should play a similarly prominent role in any strategy aimed at broader lending to the poor and the unbanked. Accordingly, we suggest that a "distribution-based" approach to access policies would allow large cohorts of potential borrowers to benefit from the positive externalities associated with recent advances in risk measurement.

The link between risk and access is not new and has been explored in a number of previous contributions on the effect of credit information on access to credit by previously rationed customers. The literature has focused at the theoretical level on the benefits that "reputation collateral" can have for potential borrowers lacking physical collateral, by reducing adverse selection (Jappelli and Pagano, 1993) and on moral hazard (Padilla and Pagano, 1997). At the empirical level, a growing body of evidence shows that the existence of credit information sharing is associated with deeper credit markets (Miller, 2003). Among this latter set of contributions, we find several references to the relevance that a proper knowledge of the distribution of good versus bad borrowers play

in broadening access to credit markets (Barron and Staten, 2003). What this literature shows is that by making use of better statistical information, the shape of the distribution of loan portfolio payoffs for any given lending policy can be improved, reducing the probability of negative occurrences.

From a different perspective, bank regulators and supervisors have been looking at the same payoff distributions, asking themselves what the risk features of different lending instruments are, to define the appropriate levels of capital requirements.

Our analysis moves from the perspective of a bank supervisor located in an emerging country, who wishes to assess the features of the loan loss distribution to determine the appropriate size of capital and loan loss reserve requirements. Such effort is justified by the fact that Basel II capital requirements are calibrated on industrialized countries' experience and may not fully capture the characteristics of credit risk in many emerging countries. In addition, a lack of internationally recognized standards for loan loss reserves makes it impossible to define a coordinated set of rules for bank capital and loan loss provisions without a thorough measurement of loan loss distributions.

This paper presents the results of an exercise jointly undertaken by the Superintendency of Banks and Financial Institutions of Chile (SBIF) and by the World Bank to provide a sound empirical basis for future solvency regulations. The relevance of these results, though, should not remain confined to the technical audience of bank regulators and supervisors because – we claim – they can shed light on the "twin" issue of access to credit services, which ranks high in the social and policy agenda as well as in the academic agenda of analysts of financial and economic growth. The distribution of credit losses in Chile is therefore explored with these "twin" objectives in mind. We can anticipate some of the main results of the paper.

<u>First</u>, the paper provides an extensive set of non-parametric estimates of expected loss (EL) and unexpected loss (UL), free from model error, i.e. from model assumptions and, in particular, from distributional restrictions. The specific advantage of the chosen approach is that it allows the estimators of EL and UL to be derived without prior assumptions about the shape of the distribution of loan losses.

Second, we empirically verify the role that loan size plays in determining the distribution of credit losses. In Chile, loans similar in size to the average per capita GDP show losses quasi-normally distributed, while larger loans exhibit asymmetric, fat-tailed, left-skewed distributions. This is not a mere statistical finding: it portends to wholly different risk management techniques for small loans, allowing for the automated processing of loan applications, whereas the traditional, manual, relationship-based processing remains appropriate where infrequent but large losses are the norm. This evidence provides a conceptual justification for the increasing automation of retail lending, and in particular of micro-lending. Also, it suggests that different solvency rules may be required for loan portfolios that exhibit radically different loan loss distributions, possibly reducing the regulatory cost of micro-lending and lowering the entry point to the provision of financial services. Overall broader opportunities exist for prospective borrowers whose loans exhibit a largely predictable payoff.

Third, our estimates cover the last upswing of the economic cycle in Chile, offering the first evidence - we believe - of cyclical behavior of ELs and ULs in emerging countries, and providing the basis for the estimation of an unconditional distribution of credit losses that may help calibrate a coherent regime of capital and loan loss reserves in Chile. At the same time, the lower cyclical sensitivity displayed by small loan portfolios' payoffs strengthens our assumption that an appropriate understanding of loan loss distributions may present households and small-sized borrowers with additional access opportunities to credit markets.

The paper is structured as follows: Section II will describe the quantitative approach followed by the SBIF to assess level and changes of credit losses in Chile. Section III provides a summary review of the recent economic cycle in Chile as a background to the following analysis. Section IV discusses the determinants of the different shape of credit loss distributions for portfolios of small and large loans. Section V shows the results of the estimation of EL and UL along the cycle. Section VI concludes, suggesting areas for future work.

II. DATA AND DERIVATION OF CREDIT LOSS DISTRIBUTIONS

Non parametric estimates of ELs and ULs of bank loan portfolios can be obtained through bootstrapping techniques as recently proposed by Mark Carey (2002) and by Majnoni and Powell (2005). These authors have suggested the usefulness of non parametric estimates as a benchmark for model-based parametric estimates of EL and UL, and for regulatory and supervisory purposes. The main advantage of these techniques rests on their independence from underlying credit risk models. This feature is particularly useful when, as in the case of credit risk, i) many competing models have been proposed, often with strong underlying assumptions; and ii) different institutional settings may not always meet the assumptions of different models. In fact, bootstrapping techniques (see Annex 1) permit the derivation of a faithful representation of the unobservable data generating process. The cost of the accuracy offered by non-parametric estimates is given by the absence of a link between the sample estimates and their structural determinants. Model-based (parametric) estimates, on the contrary, provide well identified determinants of loan loss parameters, but possibly at the cost of accurate measurements.

In the domain of credit risk measurement, important model-based alternatives are represented by the KMV model linked to Merton's option-based approach, the McKinsey macroeconomic simulation model, the Riskmetrics model – tied to observed transition matrices, the CreditRisk + actuarial approach, up to the implicit model that underlies the Basel II framework (Gordy, 2000). All of these models rely on different and often very stringent assumptions about the number of factors, the form of statistical distributions or the values of specific parameters. For these reasons, model-based estimators of EL and UL always present a margin of uncertainty due to estimation errors as well as to model errors. Estimation errors are particularly relevant in finance, where asset pricing models deal with generally unobservable risk factors whose identification is problematic and may generate a broad spectrum of misspecification errors. Model errors, instead, are linked to specific assumptions concerning the factorial structure of the model or the shape of

random variable distributions often required to simplify model solutions, but whose realism is often difficult to test[2].

There is no golden rule on the appropriate combination of non-parametric and parametric inferences. In this case, the analytical intractability of sufficiently general models of credit risk and the statistical complexity of testing the restrictions of analytically simpler models suggest the usefulness of a Montecarlo simulation approach. Sampling from the universe of past realizations will provide a faithful replica of the unobservable loan loss distribution from which historical realizations have been generated. In other words, a Montecarlo simulation gives us nothing less than an “X-ray” of the hidden distribution of credit risk and an important support in the formulation of accurate diagnostics and appropriate financial policies.

Let’s now turn to the “main assumption and definitions” adopted in the construction of the universe(s) of reference of the bootstrapping exercises.

- Universe of reference. The universe of reference is that of commercial loans to non-financial institutions granted by Chilean supervised financial institutions and censored by the Chilean Credit register. Loans are defined as the consolidated exposures of individual borrowers in place at the initial date of the analysis (December 31 of each year). The positions may include a small amount of non-performing loans (less than 5 percent of total exposures) to account for delays due to inefficiencies, rather than to inability to repay. We have then partitioned all the loans censored in the Chilean Credit Register into three dimensional categories (Table 1). The first includes loans of unit value smaller than 1 million Chilean pesos (approximately US$2,000), the second includes loans between 1 and 10 million Chilean pesos (approximately US$2,000 and US$20,000), and the third includes all the loans larger than 10 million Chilean pesos. We selected the second and third groups of loans (excluding the group with the smallest loans) as our two universes of reference. We were not able to link individual loans to the size of the borrower (as measured by sales, assets or number of employees) but, given current firm

[2] For an interesting discussion of the relevance of model risk in taking normative decisions in the domain of banking regulation see Borio and Tsatsaronis (2005).

classification in Chile[3], we can establish some broad linkages between loans and firms according to size. In particular, the first set of loans is likely to be dominated by small and micro-firms. It represents less than 3 percent of the value of outstanding loans, but over 20 percent of outstanding borrowers, indicating its modest relevance from a stability perspective, but its significantly greater importance in terms of access to financial services. The second set of loans, on the other hand, caters to the financial needs of large firms, and of the larger among medium-sized firms. With almost 97 percent of total bank loans and 12 percent of total borrowers, it has a clear systemic relevance. A further element of interest, which is discussed in detail in section IV, is that the median value of smaller loans is equal to approximately US$6,000, and coincides with the Chilean average per capita income evaluated at current prices. The median value for the universe of larger loans is ten times larger, and equals approximately US$60,000.

- Default period. Bank borrowers' behavior was observed for an entire calendar year. That is to say, the position of existing debtors as of December 31st of any specific year was analyzed during the subsequent twelve months. The study is replicated for the 7 years between December 1998 and December 2005.
- Default event. According to international practices, all debtors who, in a specific year, presented past due payments exceeding 90 days were considered in default. To avoid including delays and material errors, past due payments should involve positions exceeding 5 percent of total debt.
- Loss given default. Consistent with Basel II assumptions, a loss given default is calculated as equivalent to 50 percent of the defaulted position.

Based on the two selected loan universes we have then performed a series of Montecarlo simulations aimed at devising the distribution of credit losses for loan portfolios of standard size (in terms of the number of loans), with loans drawn respectively from one or the other of the two universes. The procedure can be phased into three steps and each sequence of step was replicated for the portfolio of large loans and

[3] Under current classification criteria in Chile, firm size according to sales is defined as follows: Micro (sales up to US$ 83,000), Small (US83,000<<US$865,000), Medium (US865,000< <US$3,460,000), Large (>US$3,460,000).

for the portfolio of smaller loans. Descriptive statistics of the two universes of reference are provided in Table 2.

The first step of the procedure consists in selecting the loans present in the Credit Register at the beginning of a given year, which do not expire in the subsequent 12 months; and their classification in two mutually exclusive categories: defaulted and non-defaulted loans. A dummy variable taking the values of 1 and 0 defines defaulted versus non-defaulted loans:

$$X = \begin{cases} 1 & \text{the borrower defaults in the reference period} \\ 0 & \text{the borrower does not default in the reference period} \end{cases}$$

The composition of the universe of larger loans between performing and non-performing loans is presented in Table 3[4].

The second step consists in the construction of a distribution of simulated portfolios' values. All portfolios feature a common and fixed number of 500 loans that is justified on statistical grounds by the size of the universe[5] and on positive grounds by the comparability with the results of similar exercises performed in previous studies by Carey (2002) and by Majnoni and Powell (2004). Value and composition of each portfolio are determined by the sum of 500 random draws without replacement from the loan universe. We have constructed 20,000 portfolios by replicating the previous exercise 20,000 times, each time with replacement. Although a number of resamplings, largely inferior to the 20,000 adopted, is considered sufficient—Efron (1988) considers that between 1,000 and 2,000 resamplings are sufficient to guarantee a close approximation of the unobserved distribution—we have resorted to this larger number of simulations to be able to measure with sufficient confidence the far tails of the distributions. Table 4 provides descriptive statistics of the distribution of the 20,000 simulated portfolios' nominal values.

[4] Due to space limitations the full set of descriptive tables have been reported only for the portfolios of larger loans.
[5] It is relevant to underline that a sample of 500 debtors is appropriate to the universe of Chilean bank borrowers, as it is associated with a level of confidence of the 99 percent and a sampling error of 3 percent, (figures that are considered sufficient to obtain good estimators of the population).

The third and final step consists in the identification of defaulted loans in each of the 20,000 portfolios[6]. Based on the number and size of defaulted loans in each portfolio, we can define the size of loan losses, as a percentage of the value of the portfolio at the beginning of the reference year, and define the frequency distribution of credit losses emerging from our 20,000 observations. Descriptive statistics of the simulated losses for the portfolio of larger loans for the seven year period are reported in Table 5. ELs and ULs were then computed from the distribution of 20,000 simulated portfolios. ELs were defined by the mean (first moment) of the loss distribution, while ULs – in line with common practices - were calculated as the difference between the value of a specific percentile and the first moment of the loss distribution. The loss identified by the selected percentile level corresponds to the maximum loss – or Value at Risk (VaR) - that the bank plans to cover with its own resources. Chart 1 shows the shape of the distribution of credit losses resulting from our simulations for the year 2005. Chart 1 shows a value of EL equal to 1.03 percent and a value of UL equal to 1.64 which overall account for a total loss of 2.67 percent that corresponds to the 95th percentile of the simulated loss distribution. The exercise has been replicated for each of the seven years 1999-2005 that cover the last ascending phase of the cycle in Chile, generating seven distributions for credit losses of large loans portfolios (Chart 2) and seven for small loans portfolios (Chart 3).

III. RECENT CYCLICAL ECONOMIC AND FINANCIAL DEVELOPMENTS IN CHILE

The main developments of the Chilean economy in our sample period are summarized below, to provide essential background before carrying out a detailed analysis of the evolution of ELs and ULs across different types of loans and across time. The years 1999-2005 span the ascending phase of the cycle of the Chilean economy.

Economic growth reached a minimum in 1999 with reduction of per capita GDP by nearly 2 percent (Table 6) and an unemployment rate of 10 percent. Starting in the year 2000, economic activity started growing again, bringing per capita GDP growth in

[6] Each portfolio can be seen as the sum of a series of 500 Bernouilli trials. If loans are of equal size these portfolios follow a binomial distribution. Consequently the distribution emerging from our 20,000 iterations may be expected to deviate from a binomial the larger is the heterogeneity of loan sizes.

2004 and 2005 close to 5 percent. Expenditure in fixed assets reached 26.6 percent of GDP after an almost 7 percentage point increase in 2005. Unemployment fell to 8 percent. After several years of depreciations, in the last couple of years the Chilean peso has begun to appreciate with respect to the dollar, while the trade balance of payments has continued to improve, favored by the boom in commodity prices.

From 2003, the acceleration of economic activity and the drop in interest rates led to a growth of bank lending (Chart 4). Despite the rapid growth of bank lending, the indicators of non performing loans kept improving. The ratio of provisions to total loans declined to 1.61 percent in December 2005, and the ratio of non-performing loans to 0.91 percent (Chart 5). Interestingly, while the deterioration of the quality of the portfolio of commercial loans, as indicated by the growth of non performing loans, came to a halt in 2000, that of personal and housing loans continued unabated until the year 2003.

On average, banks' profitability consistently recovered from the minimum touched in 1999, favored by lending growth, improved asset quality, and greater operational efficiency. Bank average ROE reached 17.9 percent in 2005 (Chart 6).

IV. CREDIT RISK EXPOSURES ACROSS DIFFERENT LOAN PORTFOLIOS AND COUNTRIES

It is now time, after the methodological and historical introductory sections above, to start analyzing in detail the shape of the distributions of the two selected groups of loans. Charts 2 and 3 and Tables 7 and 8 show the remarkable difference of loan loss distributions of bank portfolios composed by loans of different sizes. The questions that we ask ourselves are: How do we characterize these differences? Are they due to the size of loans? Are they due to the behavior of different groups of borrowers? We provide a set of tentative answers to these questions based on empirical evidence derived from our simulated distributions.

The difference between the two distributions is particularly striking (Chart 7). The loss distribution of large loans has the traditional skewed form that is expected from loan portfolios, while the distribution of small loans shows the symmetrical distribution that, according to statistical theory, should characterize portfolios with a large number of

similarly sized loans[7]. These distributional differences are particularly interesting for the policy maker as they may substantiate different financial strategies. In fact, the quasi-normality of small loans' loss curves means that the occurrence of large and infrequent losses is not an element of concern, and that lending processes can be greatly simplified, leading possibly to the automatic processing of loan applications. On the contrary, when losses are infrequent, but may be very large —as signaled by asymmetric and fat-tailed distributions, automatic processing is not to be sought as it may lead to the loss of specific but very important information. In other words a similarly effective scoring model could lead to the observed distributional differences justifying the use of different lending technologies for different (large and small) borrowers.

The difference between these distributions is largely due to the different degree of lumpiness displayed by the two portfolios. Small loans are capped by a maximum value that effectively insures a high portfolio granularity and a symmetric distribution that, for a high number of observations, converges to the normal. Very different is, instead, the unit size of large loans. These loans are not constrained by a cap, and their portfolios do not present the basic granularity conditions required for a symmetric distribution. Establishing a precise link between portfolio lumpiness and risk is not a purely statistical statement. On the contrary, it has important normative implications, since it shows why concentration limits (the equivalent of caps on loan unit value) represent an integral part of solvency requirements.[8] Analogously it provides a statistical foundation to the common practice of commercial banks of establishing loan approval limits that increase with managers' seniority and experience. Each manager would, in fact, have authority over a commonly sized pool of loans and could therefore benefit from the greater statistical regularity that characterizes the distribution of similarly sized loans. As the size

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[7] Note that the binomial distribution that characterizes portfolios of equally sized loans converges to the normal distribution for a sufficiently large number of loans.

[8] We have tested the consequences of a reduction of bank size (loan portfolio) but not of the loan size (increase in loan concentration) by cutting in half the number of loans in each simulated portfolio (250 versus 500) and measuring the resulting EL and UL. We show (Table 5, last row) that in this case the bank is hit by the "lumpiness' curse", i.e. by a strong increase in EL and UL, and consequently of capital and provisions. Measuring this largely intuitive trade-off allows definition of the appropriate coordination between minimum capital regulation and concentration limits.

of loan increases, so does the unexpected component of portfolios' losses, making seniority and access to private information the predominant criteria for loan selection.

The two sets of distributions for large and small loans show considerably different ELs and ULs. In particular, ELs are considerably larger for small loans while ULs are considerably smaller. Over our seven-year period, ELs represented 62 percent of the Value at Risk (VaR=EL+UL) of a small loan portfolio versus the 15 percent of a large loan portfolio (Chart 8). This evidence suggests that in Chile, portfolios of smaller loans have been characterized by higher but more foreseeable losses. Consequently, small loan portfolios should carry a high volume of loan loss reserves and relatively smaller capital requirements. Conversely, capital for large loans should be higher, and loan loss reserves should be smaller. Our findings—broadly in line with Basel II lower capital requirement for retail exposures—suggest that reduced capital requirements, only partially compensated for by larger loan loss reserves, provide an effective strategy to lower the cost of micro-credit and of small borrower lending. This conclusion, though, is derived from lumpiness of portfolios composition - a feature not addressed by the analytical model underlying Basel II risk assessment - and is based on the fact that only for similarly sized loans the default no-default condition can be assimilated to a Bernouilli trial and portfolio loss distributions behave as binomial distributions (and, as the number of observations grows larger, as a normal distribution).

Why then bank loans of larger size could not be grouped according to their size to obtain (as we did for the group of small loans) a series of normally shaped distributions? Unfortunately, since the number of loans decreases when their size increases, this is not possible and the distribution of credit losses does not converge to a normal distribution. In our estimation exercises, for example, the number of debtor positions available to estimate ELs and ULs decreased from approximately 178,000 for similarly sized small loans (i.e. comprised in the interval US$2,000-US$20,000) to 101,000 for loans included in the enormously larger interval between US$20,000 (Ch$10m) to US$334million (Ch$167m) (Table 2). The presence of very different loan sizes generates "lumpy" portfolios whose losses do not follow the binomial distribution: the presence of few loans of large size increases the number of large losses occurring with low probability, generating the asymmetric, fat-tailed distributions presented in Table 7 and in Chart 2.

The link between loan size and payoff distribution has an important policy implications for retail lending and household access to credit. As previously observed, symmetric, quasi-normal distributions of loan losses allow for automated loan application and processing procedures, which significantly lower risk and lending costs. It is likely that the current explosive development of retail lending and—to a minor extent—of micro-lending, that we observe in most of the developing world may be linked to the identification of loan portfolios that display quasi-normal payoff distributions.

Summarizing, our evidence suggests that the possibility of managing risk through the simple observation of statistical repayment regularities decreases rapidly as we move from small to large borrowers. Large borrowers may be subject to large and infrequent errors of judgment and may cause, therefore, large losses with low probability, requiring information intensive technologies to screen new loan applications.

Overall, different information processing technologies should be considered for the two different universes of loan instruments. "Arms' length lending" technologies are generally identified with the use of scoring models calibrated on a large number of observations, while "relationship lending" technologies rely more on ad hoc information that banks gather through the complex set of interactions with their clients.

The higher precision of forecasts about losses – and the associated lower uncertainty cost – more than offsets (in our sample) the higher cost of ELs of "arm's length lending" to large numbers of small borrowers suggesting that the application to emerging countries of largely tested retail lending techniques based on scoring procedures may lead to a lower cost of lending and/or to a larger availability of credit to previously rationed customers. The broad supply by US banks of "pre-approved" credit card to low income customers may be an example of these policies in a developed country.

The open question is then: which loans and of what size can benefit from "arm's length lending" technology in different countries? Our evidence suggests that the answer should largely be based on bank loans concentration more than on loan size *per se*. For example, it is difficult to imagine that the loan distribution by size may peak at values

equal to several multiples of a country's per capita income. The opposite appears more likely. What matters may therefore be the relationship between the nominal or real value of a loan and a country's income level and distribution. We provide some additional motivation for the existence of a link between income distribution and the risk feature of loan portfolios in Annex 2. Nature and relevance of this link needs to be explored in greater detail before deriving any policy implications but it is clear that people belonging to densely populated income classes may enjoy (relatively more) favorable conditions of access to credit, for any given level of ELs.[9]

Most of the previous considerations are related to loan size independently from institutional considerations. Bootstrapping techniques, however, permit verification of the claim that different institutional frameworks affect banks' risk exposure, comparing EL and UL of otherwise similar portfolios in different countries. We did not have sufficient cross country evidence to further explore this point, so we had to limit our cross country comparison to only two countries (Argentina and Chile) and to only the period where we had comparable data. The results presented in Table 9 allow us to compare the different features of credit risk during two crisis years in Chile, the year 1998 (when EL reached a maximum) and 2000 (when UL reached a maximum) and one crisis year in Argentina, the year 2001, which preceded the fall of the convertibility plan. The different degree of severity of the systemic crises in Argentina and Chile are clearly revealed by the different level of ELs and ULs.

The empirical evidence presented in this section suggests that, where loan size is small with respect to total portfolio, the loss distribution is a) symmetric, b) requires higher levels of provisions but lower levels of capital, and c) is relatively insensitive to the cycle. The reverse is true when loan size increases with respect to the size of the bank. It is likely that a distribution-based loan classification could be of help in detecting the appropriate lending technology. Although our results are indicative of policy and regulatory developments, they should be interpreted with caution for several reasons.

[9] The main challenge deriving from the link between income distribution and loan distribution is that for very low income countries income cluster may be found for very low income levels preventing the exploitation of scale economies and the supply of credit.

First, the severity of loan losses can vary across different assets and different institutional settings, a feature not considered in this paper, where we have assumed an invariant 50 percent Loss Given Default (LGD) ratio. Second, EL and UL are generally affected by risk management capacity and it is therefore possible that the risk exposure of randomly selected portfolios may over or underestimate the risk exposure of a specific bank. Third, considerably more evidence should be gathered for countries with different per capita income levels to better understand how different lending technologies can spread across countries, broadening access to financial services without reducing stability.

V. Credit loss distribution over the economic cycle

Credit loss distributions along the economic cycle depend on the prevailing macroeconomic conditions. Our seven-year sample period spans the upswing phase of the cycle in Chile and permits us to observe how changes in the economic conditions affect loan loss distributions. Chart 3 shows the sequence of annual loss distributions for larger loans. At the start of the period, which marked the low point of the cycle, the curve has a flat shape and a marked fat tail. Over time, as the economy recovers and moves toward the peak of the cycle, the shape of the curve changes, acquiring a steeper slope and a thinner tail, and correspondingly smaller values of expected (the mean) and unexpected (the selected percentile level) losses. The results obtained for the period of seven years between December 1998 and December 2005 offer the first evidence, to our knowledge, of the behavior of credit losses along the cycle in an emerging economy. Table 7 presents the time series of ELs and ULs derived from the same distributions, with ULs measured at the level of the 95th, 99th and 99.9th percentiles. Three main observations can de derived from the gathered evidence.

First, we observe that ELs shrank from 2.8 to 1.0 percent of the loan portfolio, or to almost one-third of their value going from the trough to the peak of the cycle. This suggests the importance of a pro-cyclical provisioning policy that could offset the oscillations of EL by requiring a replenishment of loan loss reserves in good times (for

example from 1.0 to 2.8 percent of the loan portfolio) and allowing a reduction in bad times (for example from 2.8 percent to 1.0 percent)[10].

Second, ULs too became smaller. Measured at the level of the 99.9 percentile, they went from 12.4 to 10.1 percent of the loan portfolio with a reduction of almost 25 percent. These figures refer to "leverage" ratios (i.e. Tier 1 capital over total loans) and therefore suggest a quite demanding level of capital requirements. Table 7 shows that levels of protection between 95 percent and 99 percent would be more realistic in the case of Chile and more coherent with capital requirements of 4 percent (Basel requirement for Tier1 capital).

Third, what differentiates this pattern from that of portfolios of small loans, reported in Chart 3 and Table 8? The main feature worth stressing is the greater stability of both ELs and ULs displayed by portfolios of small loans across the cycle. These portfolios displayed oscillations of ELs around the mean of approximately 10 percent, considerably smaller than the 30 percent of large loan portfolios. Similarly, the oscillations of ULs around the sample mean reached 5 percent for small loans and approximately 20 percent for larger loans. The greater stability of the distribution of loan losses for small loan portfolios can be very clearly spotted in the sequence of panels of Chart 9, where we have reported the evolution of the two distributions for each year of our sample period.

The greater cyclical stability displayed by small loan portfolios reinforces the elements which already emerged in the previous section in favor of the automation of loan application procedures. In fact, credit loss distributions for short term loans appear to be less sensitive to variations of the level of economic activity. In contrast to the previous section, where the regularity of the distribution of loan losses was attributed to statistical factors, in this case the causes of the observed stability should be found in different repayment patterns linked to the different economic behavior of households and firms of different size during the different phases of the economic cycle.

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[10] See Laeven and Majnoni (2003) for a survey of the debate on loan loss provision smoothing over the economic cycle.

VI. Conclusions

Changes of expected and unexpected loan losses over time and across different loan portfolios reflect differences in the underlying loan loss distribution. This paper has provided a measure of loan loss distributions for selected bank loan portfolios, based on data from the Chilean Credit Register, and has shown the different features of loan loss distribution of large and small loans as a possible guide to appropriate risk and access policies.

We believe that these estimates provide the first detailed evidence of how ELs and ULs behave over the cycle and across different loan portfolios for an emerging country. Moreover, the evidence presented in this paper suggests relevant regulatory developments that could better tailor solvency and provisioning rules to the risk of different categories of borrowers and sizes of loans. We suggest that a "distribution-based" approach could provide powerful tools to distinguish loan portfolios whose efficient management should rely on "relationship" lending technologies (characterized by asymmetric distributions) from those that should instead rely on "arm's length" lending technologies (characterized by quasi-normal distributions).

While the implication of different loan portfolio payoffs appears to have been studied in depth by bank risk managers and supervisors, this does not appear to have been the case for policymakers interested in deepening the banking market. We claim that this is an important omission because the empirical evidence may help detect when loans reap the benefits of diversification and access can be broadened without negative profitability consequences.

We conjecture that the main features of loan distribution are linked to those of income distribution. Although this proposition can be tested only with a cross country dataset some of its implication may be anticipated. In the first place bank credit polarization around small loans may provide favorable conditions for cheaper and broader supply of credit to the low income segment of the population. In addition, it is to be expected that the growing inequality of income distribution that takes place during economic contractions may play an independent negative affect on the cost and

availability of credit. We have not ventured into the normative implications of our results. This is a more complex task for which additional evidence is required.

Areas for future work include the analysis of the loss distributions of portfolios of intermediate-sized loans related to different categories of borrowers in order to better detect the border line between “relationship” lending and “arm’s length” lending. A better understanding of this distinction, in turn, may help identify credit instruments suitable to reach potential borrowers, currently barred from bank credit, while limiting the impact of credit growth on systemic stability. The current acceleration of consumer credit throughout the developing world, and the more moderate and uneven growth of commercial lending may well be due to the identification of the different bank portfolio pay offs of the two loan categories, and to the transfer of new retail lending technology from more advanced banking systems to emerging markets. A formal test of this hypothesis represents an additional topic for future research.

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ANNEX 1. Bootstrapping Method

The key steps of a bootstrapping estimation procedure are:

1. Generate an empirical distribution probability, $\hat{F}(x)$, from a sample assigning probability equal to 1/n at each point, x_1, x_2, ..., x_n. This is the empirical distribution function (EDF) of *x*, which is the non-parametric maximum likelihood estimator of the population distribution function, *F(X)*.

2. From the EDF, $\hat{F}(x)$, a simple random sample of size n with replacement is extracted. This is the x_b^* "resample".

3. The statistic of interest $\hat{\theta}$ is calculated from that resample, obtaining $\hat{\theta}_b^*$.

4. Steps 2 and 3, are repeated *B* times, where ***B*** is a large number (the actual size of *B* depend on the tests that will be conducted on the data. In general, *B* should be between 50 and 200 to estimate the typical error of $\hat{\theta}$, and of at least 1.000 to estimate confidence intervals around $\hat{\theta}$ (Efron y Tibshirani, 1986, 1993)).

5. Generate a probability distribution from all *B*, $\hat{\theta}_b^*$ assigning a probability of *1/B* at each point, $\hat{\theta}_1^*$, $\hat{\theta}_2^*$, ..., $\hat{\theta}_B^*$. This distribution is the bootstrap estimation of the sampling distribution of $\hat{\theta}^*$, $\hat{F}^*(\hat{\theta}^*)$. This distribution can be used to estimate θ.

6. The bootstrap estimator of the parameter θ is defined as the average of the statistic's values calculated in the B bootstrap resamples:

$$\hat{\theta}_{(.)}^* = \frac{\sum_{b=1}^{B} \hat{\theta}_b^*}{B}$$

Observation: In our study:

$$\hat{\theta}_b^* = \frac{\sum_{i=1}^{500} Losses}{\sum_{i=1}^{500} Exposures} = Percentage\ of\ estimated\ Loss$$

Then, the bootstrap estimator is given by the average of the estimated loss calculated in each of the 20.000 sample, as shown:

$$\hat{\theta}^* = \frac{\sum_{b=1}^{20000} \hat{\theta}_b^*}{20000} = PE$$

It is important to point out that the number of 20.000 samples was selected to replicate studies already performed in other countries and to allow the inclusion of the largest possible combination of debtors.

ANNEX 2. Income and Loan Size Distributions

The link between income distribution and the distribution of bank loans by size may provide useful information for extending bank credit to new cohorts of customers. For instance, a detected link between the modes of the income and of the loan-size distributions could be exploited across countries potentially favoring a broader "bankarization" in those countries where bank lending has been limited to large borrowers. In fact, from income distribution we could infer which loan size could most likely benefit from statistical regularities and from the adoption of cost effective "arm's length" lending technologies. We provide two different motivations for a link between income and loan size distribution: the first relevant for individuals and small family businesses, the second for larger non financial firms.

In the first case, the link between loan value and income can be intuitively derived from the conditions for dynamic convergence of public debt[11]. Banks, in fact, will not lend to borrowers whose debt exceeds their repayment capacity, just as investors will not underwrite bond issues of sovereigns whose debt does not meet stability conditions. The loan to income ratio plays for individuals the same role the debt to GDP ratio plays in insuring debt sustainability at a macro level (Blanchard, 1990). In particular, we can say that a bank will, on average, consider an individual or a household in good standing if their debt to per capita GDP ratio (d) is smaller than their saving rate (s) divided by the difference between the charged real interest rate (r) and per capita GDP growth (g):

$$d < s/(r - g) \qquad (1)$$

When equation 1) becomes binding (holds as an equality), the equilibrium debt/income ratio is affected negatively by the excess of the real rate over economic growth and positively by the saving rate. In this simplified setting, countries with similar s/(r-g) ratios and similar income distributions would present similar payoff distributions for loans representing a common multiple of per capita GDP. Should the debt/income ratio (d) be equal to 1 across countries one would expect to find similar distributions for loans of very different size but equal to per capita GDP (i.e. US$ 30,000 loan in the USA, US$ 6,000 in Chile, US$ 2,500 in Brazil or US$ 300 in Haiti) (Chart 10). This would justify the application of the same lending technology to loans which, although progressively smaller in nominal terms, have a common link to the repayment capacity of the most densely populated income class in a given country. What relationship exists in the

[11] It is also important to recall that in our empirical exercises loan exposures represent the total bank debt of a borrower with the banking system as a whole.

more complicated real world where equation 1 holds as an inequality is a matter for future research.

The identification of a link between income distribution and loan distribution for firms grows in complexity with firm’s size. Still, also non-financial firms – other things equal - should be getting better access to bank credit when they grow in number. The modal value of income distributions would again indicate the category of borrowers that are most likely to benefit from “arm’s length” lending. In practice many factors play against the identification of a clear link between firm’s income distribution and loan-size distribution: the need to distinguish between different productive sectors, capital intensities, exposure to the economic cycle.

A final point concerns the appropriate comparison of firms’ size across countries to have a consistent classification of family business (more affected by income distribution), small and large firms (less affected by income distribution). Comparisons in real terms are often made difficult by to the lack of widely available real variables. The number of employees, for example, is seldom available or misleading where the informal sector is very relevant. Normalization by per capita GDP appears the simplest solution. Table 10 illustrates this point. In the first column we have reported the sales-value that corresponds to the upper and lower limit of SMEs, as defined by the Basel Committee and the European Commission. These values represent different multiples of G10 countries per capita GDP. More specifically 5,000 and 50,000 euros would correspond to approximately 20 and 200 percent of the average per capita income in the G10 countries. The following columns (from the second to the sixth) report the sales value obtained applying the same multiples of per capita GDP to countries belonging to different income group levels. The table shows how different firms’ size may be across income groups also for those firms that, due to the link between sales and labor costs, are likely to have a similar size in terms of their use of productive factors.

Table 1

Loans in the Credit Register: Size Composition

Years	Number of Borrowers				Size of the Debt			
	<$1M	$1M < $10M	>$10M	Total	<$1M	$1M < $10M	>$10M	Total
					Values in thousands			
1999	509	154	93	756	129	486	17669	18284
2000	528	161	96	786	139	498	17984	18621
2001	572	177	100	849	155	537	19621	20312
2002	626	188	104	918	174	556	21105	21836
2003	665	191	105	962	182	570	21447	22199
2004	681	197	108	985	184	587	21829	22600
Average	597	178	101	876	161	539	19942	20642
					Percentage values			
1999	67.30	20.37	12.33	100.00	0.71	2.66	96.64	100.00
2000	67.26	20.52	12.22	100.00	0.74	2.67	96.58	100.00
2001	67.34	20.90	11.76	100.00	0.76	2.64	96.60	100.00
2002	68.27	20.45	11.28	100.00	0.80	2.55	96.66	100.00
2003	69.15	19.89	10.96	100.00	0.82	2.57	96.61	100.00
2004	69.11	19.96	10.94	100.00	0.81	2.60	96.59	100.00
Average	67.28	20.45	12.28	100.00	0.73	2.67	96.61	100.00

Table 2

Universe of Loans: Descriptive Statistics

(Millions of Chilean pesos)

Year	Number of loans	Mean	Median	St. Dev.	Min. value	III decile	V decile	VII decile	VIII decile	IX decile	Max. Value
	Loans > 10 million Chilean pesos										
1999	86,685	181	29	1,369	10	18	29	53	82	177	95,203
2000	88,826	179	29	1,441	10	18	29	52	80	169	99,902
2001	90,790	189	29	1,654	10	18	29	52	79	167	114,849
2002	95,774	198	29	1,793	10	19	29	53	80	165	121,923
2003	96,705	201	29	1,907	10	19	29	52	78	159	153,994
2004	97,797	201	29	1,995	10	18	29	51	77	158	148,637
2005	99,880	215	29	2,125	10	18	29	52	80	169	166,895
	Loans < 10 million Chilean pesos										
1999	142,823	3.14	2.23	2.27	1	1.53	2.23	3.64	4.93	6.88	10
2000	149,338	3.07	2.12	2.25	1	1.50	2.12	3.50	4.78	6.78	10
2001	164,960	3.00	2.08	2.20	1	1.49	2.08	3.36	4.60	6.59	10
2002	173,441	2.95	2.05	2.18	1	1.47	2.05	3.27	4.49	6.48	10
2003	176,028	2.96	2.05	2.18	1	1.47	2.05	3.28	4.52	6.48	10
2004	180,803	2.96	2.06	2.17	1	1.47	2.06	3.29	4.51	6.44	10
2005	122,366	3.47	2.68	2.34	1	1.74	2.68	4.26	5.40	7.25	10

Note: Loans are equal to the consolidated performing debt of commercial borrowers only (non financial private sector) with financial supervised intitutions (banks & non banks) at the beginning of the reference year.

Table 3

Loans Larger than Ch$10 Million: Share of Performing Borrowers

(Millions of Chilean pesos)

Reference Year	Total Number of borrowers	Solvent Borrowers Number	Solvent Borrowers %	Insolvent Borrowers Number	Insolvent Borrowers %
1999	86,685	78,954	91.0	7,731	8.9
2000	88,826	81,755	92.0	7,071	8.0
2001	90,790	83,737	92.2	7,053	7.8
2002	95,774	88,107	91.9	7,667	8.0
2003	96,705	88,185	91.1	8,520	8.8
2004	97,797	90,951	93.0	6,846	7.0
2005	99,880	94,703	94.8	5,177	5.2

Note: Loans are equal to the consolidated performing debt of commercial borrowers only (non financial private sector) with financial supervised institutions (banks & non banks) at the beginning of the reference year.

Table 4

Simulated Portfolios Values: Descriptive Statistics

(Millions of Chilean pesos)

Year	Loans in the portfolio	Mean	Median	St. Dev.	Min. value	III decile	V decile	VII decile	VIII decile	IX decile	Max. Value
1999	500	90,650	84,221	30,869	31,124	71,909	84,221	100,125	111,985	131,655	399,990
2000	500	89,554	82,453	32,141	28,119	69,708	82,453	99,508	112,211	133,116	294,947
2001	500	93,900	85,515	36,645	34,795	71,605	85,515	103,763	118,010	142,614	401,974
2002	500	99,035	90,019	39,746	32,258	74,382	90,019	110,970	126,335	152,518	356,198
2003	500	99,922	90,130	41,862	30,713	73,828	90,130	112,112	128,565	155,609	441,068
2004	500	100,420	89,134	44,820	30,715	72,670	89,134	111,563	128,662	159,378	420,832
2005	500	107,481	95,660	47,252	34,940	78,210	95,659	119,512	138,003	170,559	543,580

Note: Portfolio are composed of loans larger than Ch$10 million. Loans are equal to the consolidated performing debt of commercial borrowers only (non financial private sector) with financial supervised institutions (banks & non banks) at the beginning of the reference year.

Table 5

Simulated Portfolio Losses: Descriptive Statistics

(Percentage values)

Year	Loans in the portfolio	Mean	Median	St. Dev.	Min. value	III decile	V decile	VII decile	VIII decile	IX decile	Max. Value
1999	500	2.81	2.23	2.00	0.25	1.63	2.23	3.11	3.85	5.19	20.16
2000	500	2.58	2.10	1.77	0.21	1.53	2.10	2.92	3.58	4.76	18.93
2001	500	2.32	1.79	1.94	0.19	1.30	1.79	2.51	3.11	4.22	24.60
2002	500	2.49	1.94	1.89	0.20	1.38	1.94	2.79	3.48	4.73	20.91
2003	500	1.96	1.51	1.64	0.18	1.12	1.51	2.09	2.57	3.53	21.63
2004	500	1.35	1.03	1.17	0.08	0.75	1.03	1.41	1.75	2.45	14.17
2005	500	1.03	0.75	1.00	0.05	0.54	0.75	1.08	1.36	1.96	17.66
2005	250	1.13	0.72	1.44	0.03	-	-	-	-	-	-

Note: Portfolio are composed of loans larger than Ch$10 million. The recovery rate has been set at 50% of the loan value.

Table 6

Chile: Main Economic Indicators

	1997	1998	1999	2000	2001	2002	2003	2004	2005[e]
Real GDP[a]	6,6	3,2	-0,8	4,5	3,4	2,2	3,7	6,1	6,0
Per capita GDP[a]	5,1	1,9	-2,0	3,2	2,2	1,0	2,6	4,9	4,9
Unemployment[b]	6,1	6,2	9,7	9,2	9,2	9,0	8,5	8,8	8,1
Exchange Rate[c]	417,9	457,4	503,8	536,1	627,8	687,9	710,9	601,9	559,8
BOP Trade Balance[d]	-1.428	-2.040	2.427	2.119	1.843	2.386	3.522	9.019	9.113
BOP Current Account [d]	-3.660	-3.918	100	-898	-1.100	-580	-1.102	1.390	269
Private External Debt[d]	5.088	5.714	5.827	5.522	5.759	7.197	5.421	6.286	nd
Public External Debt[d]	21.613	25.977	28.285	30.955	32.273	33.198	37.975	37.478	nd

(a) Yearly rate of change; (b) Percentage; (c) Pesos per dollar (d) Million of dollars; (e) Preliminary data.

Table 7.

Distribution of Credit Losses: Large Loans Portfolios

(Percentage values)

Year	Portfolio Size	PD	Expected Loss (EL)	Unexpected Losses (ELs) 95% Confidence Interval	99% Confidence Interval	99,9% Confidence Interval	Minimum Loss	Maximum Loss
1999	500	5.61	2.81	3.90	7.83	12.42	0.25	20.16
2000	500	5.15	2.58	3.36	6.39	12.01	0.21	18.93
2001	500	4.63	2.32	3.27	8.29	15.79	0.19	24.60
2002	500	4.97	2.49	3.63	7.19	12.86	0.20	20.91
2003	500	3.93	1.96	2.91	7.14	12.29	0.18	21.63
2004	500	2.70	1.35	2.05	5.22	9.00	0.08	14.17
2005	500	2.05	1.03	1.64	3.71	10.13	0.05	17.66
Average	-	4.15	2.08	2.97	6.54	12.07	0.17	19.72
St. Dev.	-	1.33	0.67	0.83	1.60	2.15	0.07	3.28

Note: Portfolio are composed of loans larger than Ch$10 million. The recovery rate has been set at 50% of the loan value.

Table 8.

Distribution of Credit Losses: Small Loans Portfolios

(Percentage values)

Year	Portfolio Size	PD	Expected Loss (EL)	Unexpected Losses (ELs) 95% Confidence Interval	99% Confidence Interval	99,9% Confidence Interval	Minimum Loss	Maximum Loss
1999	500	8.95	4.48	1.35	2.01	2.69	1.91	7.86
2000	500	7.42	3.71	1.28	1.85	2.45	1.00	6.67
2001	500	8.36	4.18	1.32	1.91	2.62	1.63	8.01
2002	500	8.74	4.37	1.36	1.98	2.71	1.80	7.94
2003	500	9.76	4.88	1.43	2.09	2.80	1.93	8.63
2004	500	7.23	3.61	1.26	1.85	2.59	1.08	6.88
2005	500	8.83	4.41	1.27	1.86	2.51	1.67	7.73
Average	-	8.47	4.23	1.33	1.93	2.62	1.58	7.68
St. Dev.	-	0.89	0.45	0.06	0.09	0.12	0.38	0.68

Note: Portfolio are composed of loans larger than Ch$1 million and smaller than Ch$10 million. The recovery rate has been set at 50% of the loan value.

Table 9.

Expected and Unexpected Losses in Argentina and Chile

(Percentage values)

Country/Year	Default Probability	Expected Losses (EL)	Unexpected Losses (ULs) 95%	99%	99.9%
Argentina (Dic 2000-Dic. 2001)	9.6	4.8	7.3	14.8	21.8
Chile (Dec 1998-Dic 1999)	5.6	2.8	3.9	7.8	12.4
Chile (Dec 2000-Dic 2001)	4.6	2.3	3.3	8.3	15.8

Source: SBIF and Majnoni and Powell (2005)

Table 10.

SME's sales normalized by per capita income levels by income group countries [1/]

Firm size by Sales	G-10[2/]	Upper-Middle[3/]	Middle		Lower-Middle[5/]	Low[6/]
			Total[4/]	Chile		
Medium	50,000,000	12,189,659	8,340,293	8,133,399	4,489,029	262,840
Small	10,000,000	2,437,932	1,668,059	1,626,680	897,806	52,568
Micro (Basel II)	5,000,000	1,218,966	834,029	813,340	448,903	26,284
Micro (EU Commission)	2,000,000	487,586	333,612	325,336	179,561	10,514

[1/] The classification of SME has follows the new SME definition from the European Commission. Values refer to the maximum level of sales for each category (i.e. medium size firms have sales up to 50,000 euro in the EU). '2/ Belgium, Canada, France, Germany, Italy, Japan, Netherlands, Sweden, Switzerland, UK, and USA. '3/ Only the top 15 countries of the upper-middle income group are included. '4/ Only the top 15 countries of the lower-middle income group are included. '5/ Average of the GDP per capita of the countries considered in the upper-middle and lower-middle group. '6/ Only the top 15 countries of the low income group are included (excluding Equatorial Guinea whose GDP per capita is 4825 Euros for 2004).

Chart 1

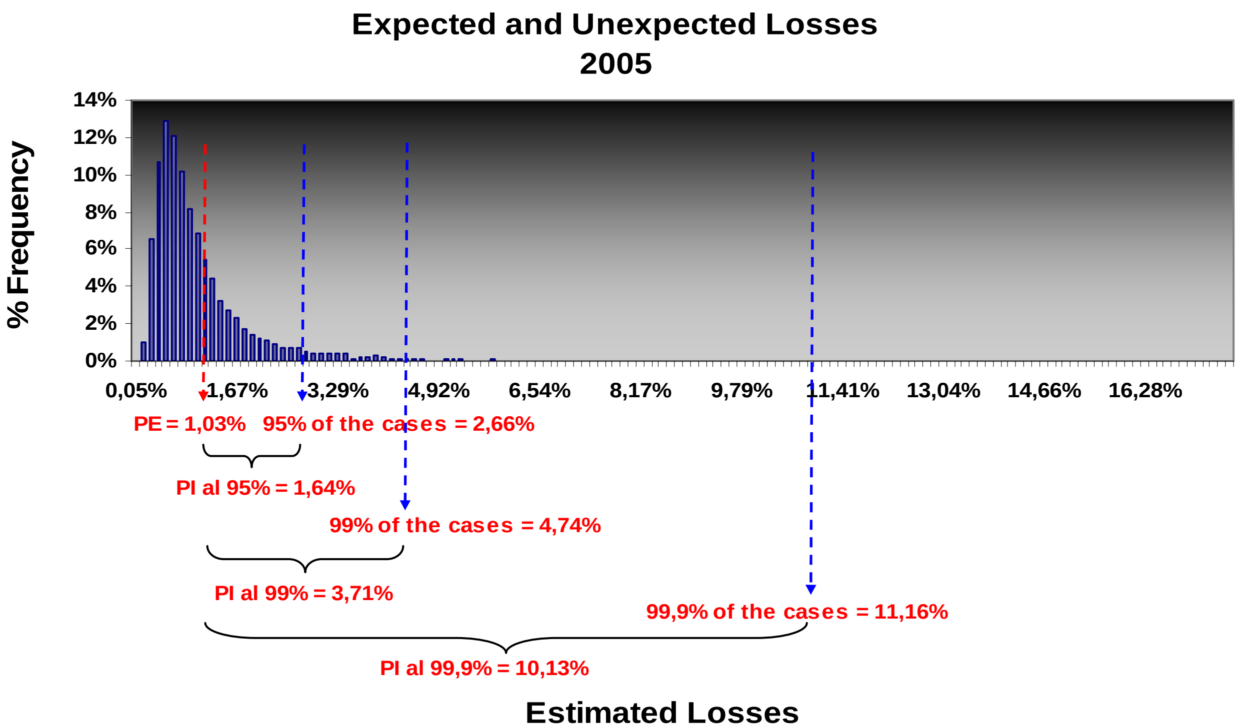


Chart 2

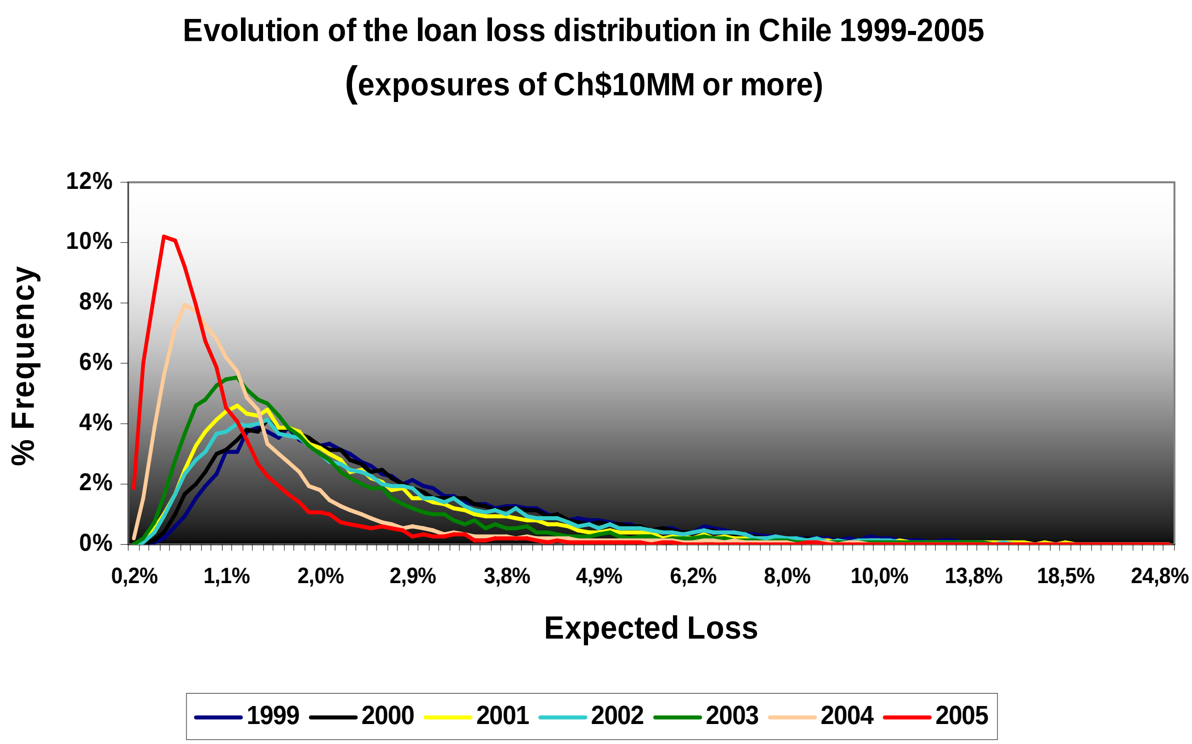


Chart 3

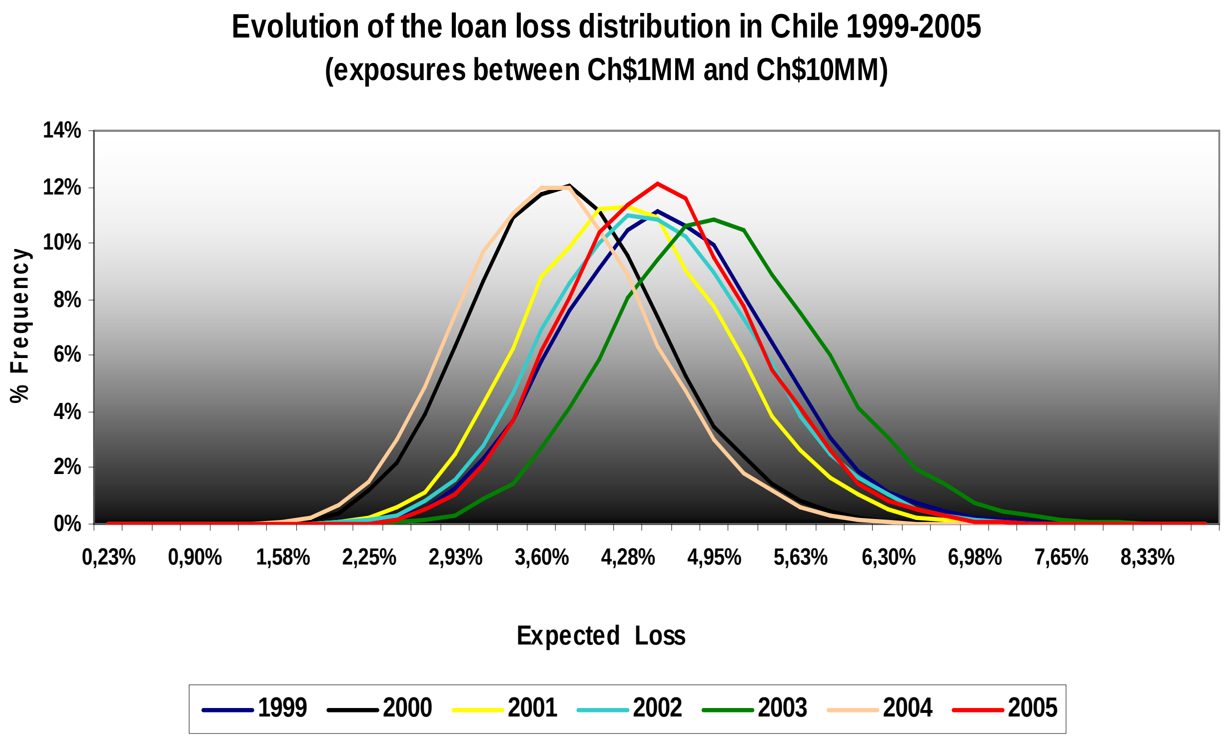


Chart 4 **Total and Commercial Lending: 12 Month Growth Rate**

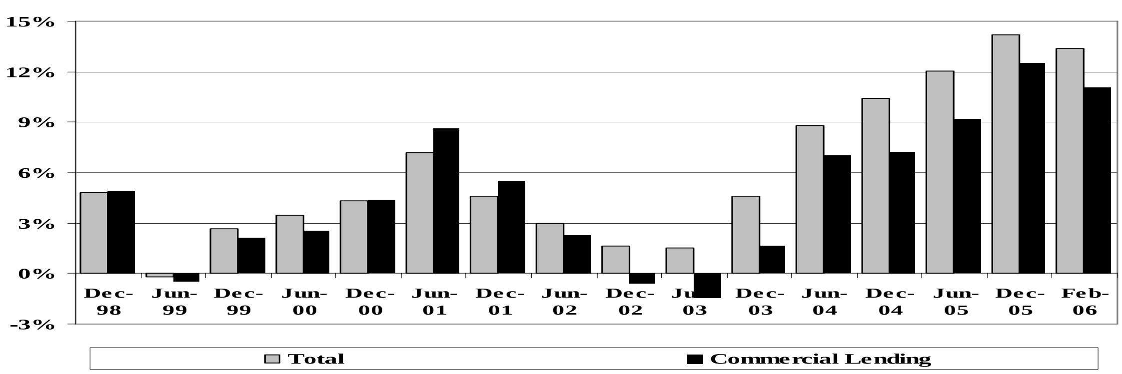


Chart 5 Non Performing Loans by Category: 12 Month Growth Rate

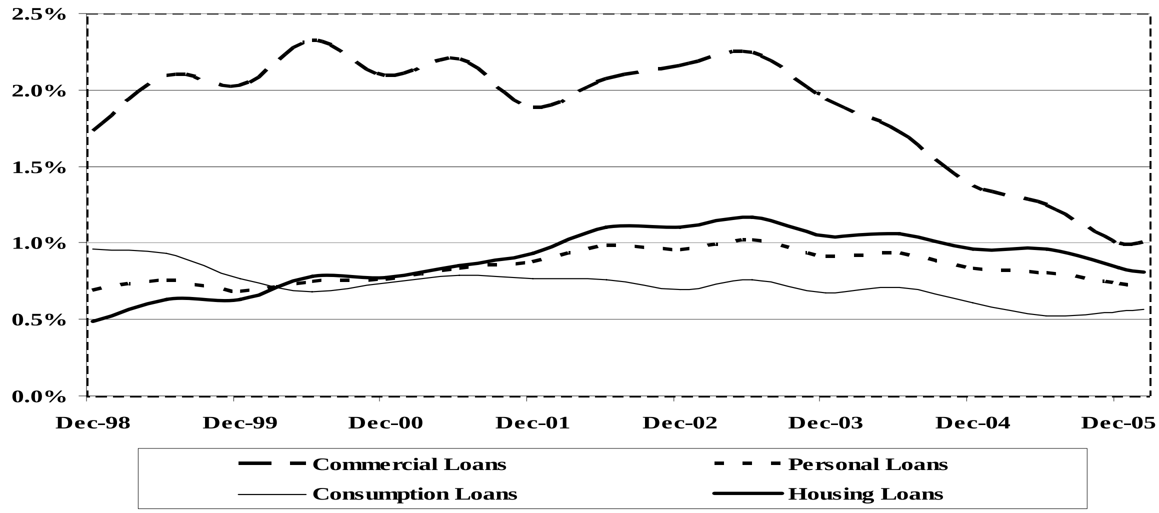


Chart 6 Bank Profitability (ROE) and Efficiency

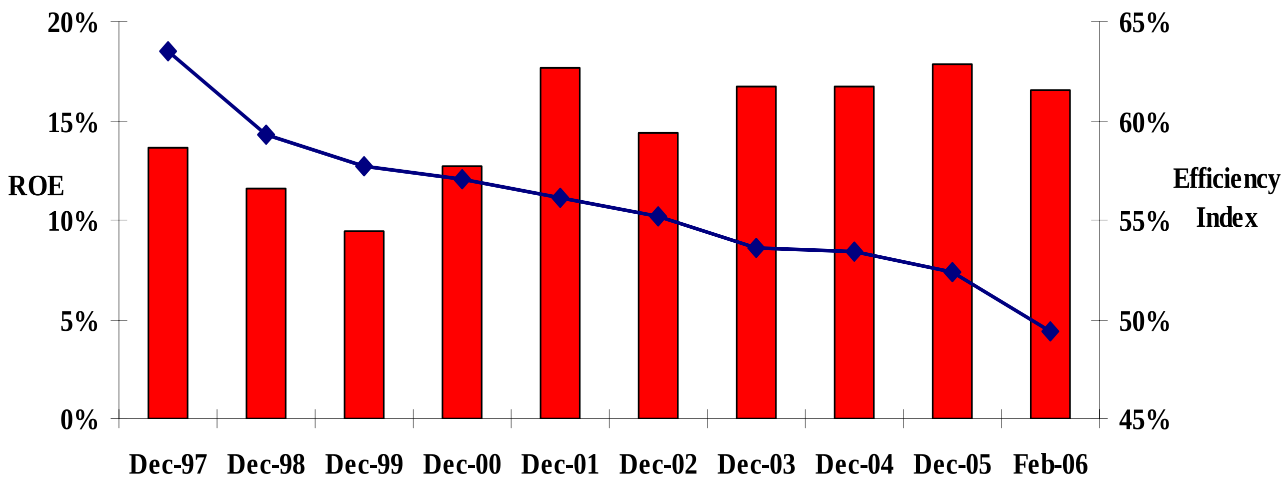


Chart 7 Credit loss distributions for portfolios of large and small loans

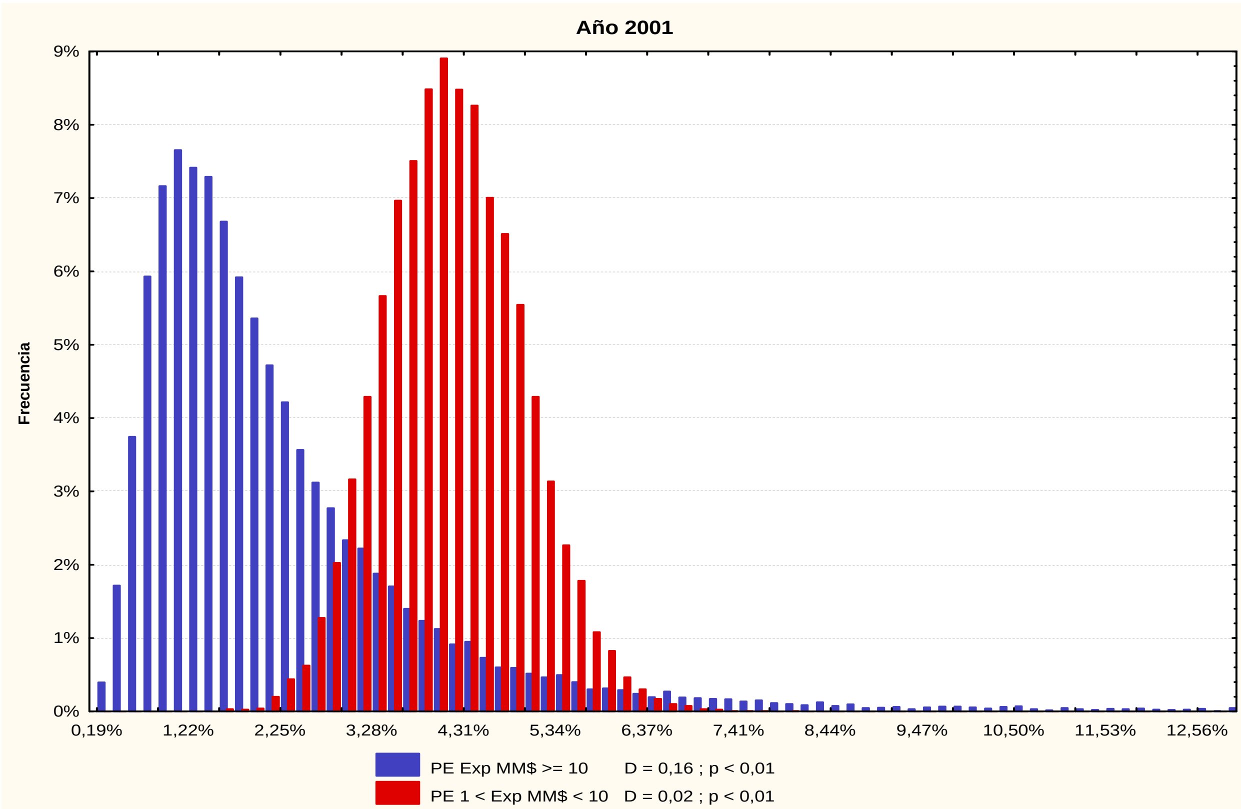


Chart 8

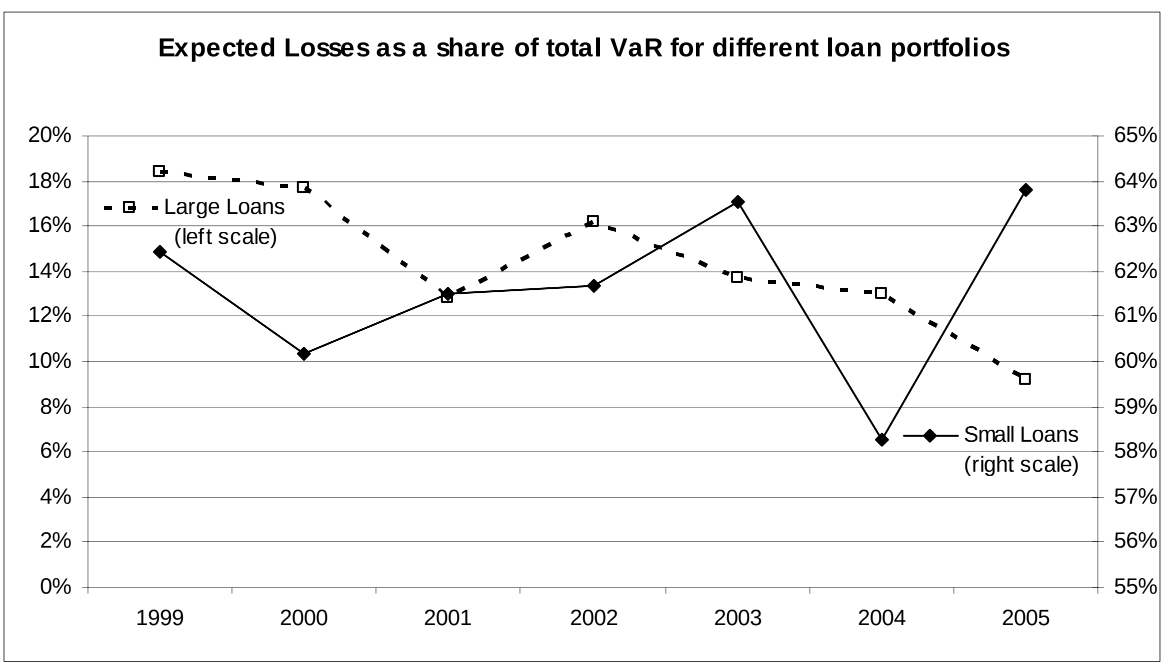


Chart 9 **Distributions of portfolio losses with loans larger or smaller than Ch$ 10 million.**

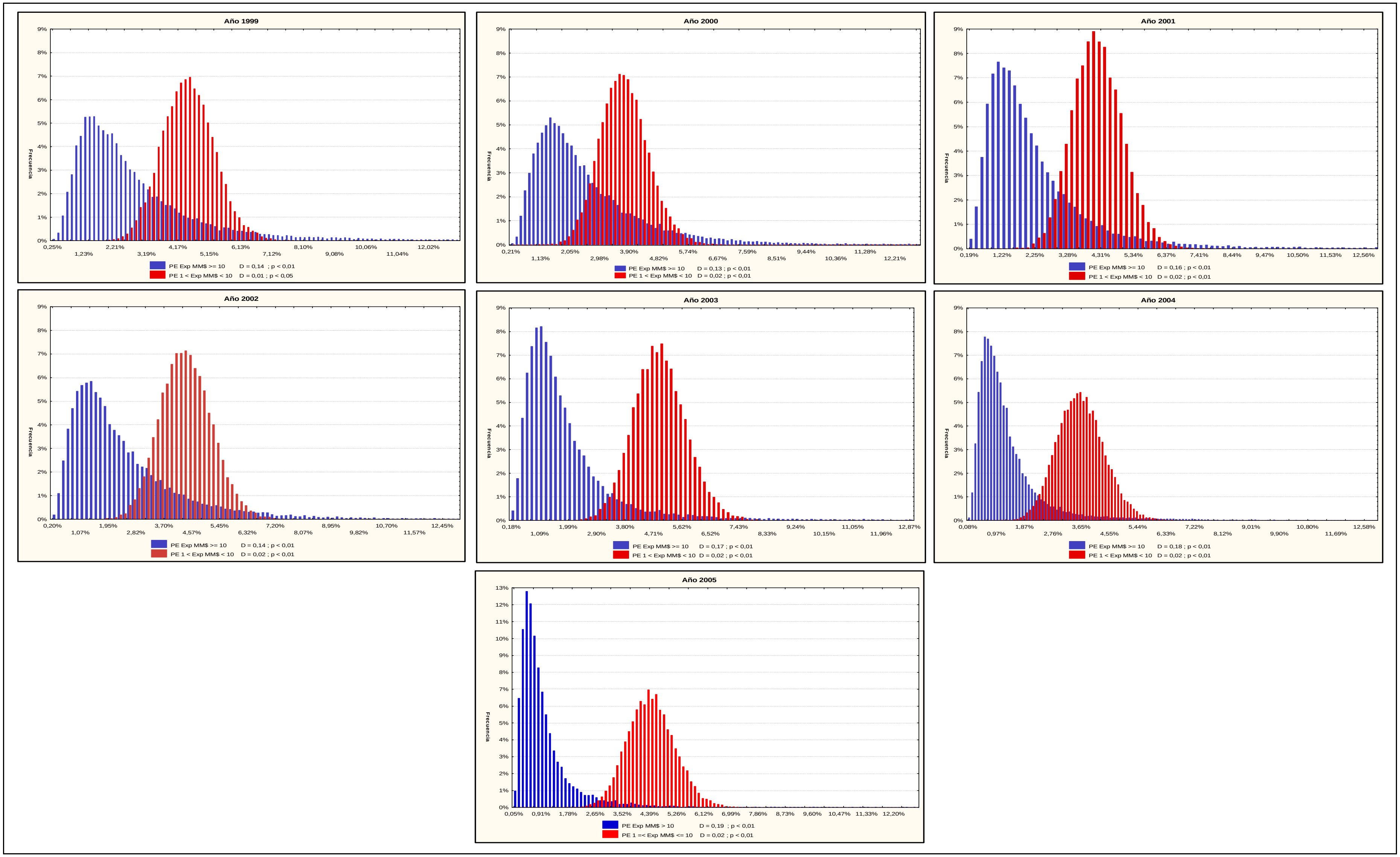
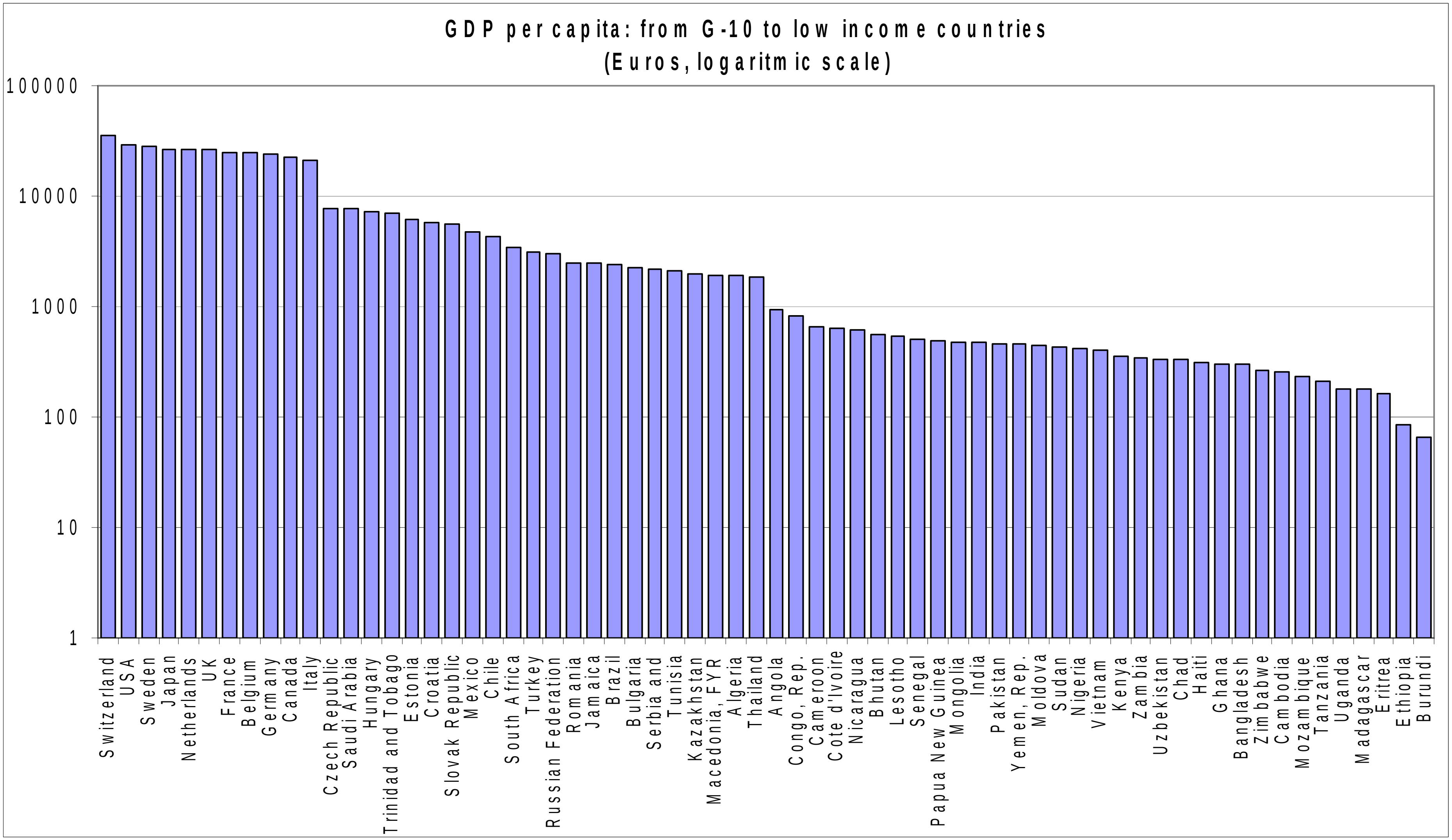


Chart 10


GDP per capita: from G-10 to low income countries
(Euros, logaritmic scale)
100000
10000
1000
100
10
1
Switzerland
USA
Sweden
Japan
Netherlands
UK
France
Belgium
Germany
Canada
Italy
Czech Republic
Saudi Arabia
Hungary
Trinidad and Tobago
Estonia
Croatia
Slovak Republic
Mexico
Chile
South Africa
Turkey
Russian Federation
Romania
Jamaica
Brazil
Bulgaria
Serbia and
Tunisia
Kazakhstan
Macedonia, FYR
Algeria
Thailand
Angola
Congo, Rep.
Cameroon
Cote d'Ivoire
Nicaragua
Bhutan
Lesotho
Senegal
Papua New Guinea
Mongolia
India
Pakistan
Yemen, Rep.
Moldova
Sudan
Nigeria
Vietnam
Kenya
Zambia
Uzbekistan
Chad
Haiti
Ghana
Bangladesh
Zimbabwe
Cambodia
Mozambique
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