Constrained Banks and Constrained Borrowers:
Does Bank Liquidity Affect Loan Growth, Collateral and Default Risk?

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Abstract. *Financing frictions affect banks' ability to lend and may hinder the flow of funding to profitable bank dependent firms. At the same time, financial constraints may arise optimally to prevent banks from taking too much risk. This paper sheds light on the nature of bank financing frictions by looking at how loan growth and risk react to an exogenous expansion in available financing caused by a government credit market intervention in Argentina. Using monthly bank balance sheet data between 1996 and 2000, I estimate a loan-liquidity sensitivity in the order of $0.7 per dollar of liquidity expansion. I replicate previous estimates of this sensitivity using deposits as the source of the shock and show they are downward biased. Then I match the bank data with a credit bureau loan level dataset and show that when banks face a positive liquidity shock they relax collateral requirements to new borrowers and expand lending to known borrowers with worse histories of repayment performance. Finally, I show that although low collateral and bad credit histories are good predictors of default on average, loans made during liquidity expansions are not more likely to default. The results are consistent with the sub-optimal lending view of financing constraints.*

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"There is an inconsistency in assuming that when you give your money to a financial institution there is no agency problem, but when you give it to a firm there is."

Franklin Allen, 2001
Presidential Address - JOF

Financing frictions affect banks' ability to lend and may hinder the flow of funding to profitable bank dependent firms. At the same time, financial constraints may arise optimally to prevent banks from taking too much risk. This paper exploits the theoretical prediction that financially constrained banks will have a positive lending-liquidity sensitivity to evaluate constrained banks' marginal loan allocation rules and risk. A government *on-lending* program in Argentina provides a shock to liquidity that is uncorrelated to changes in investment opportunities, shocks to deposits or other factors that may affect lending. This natural "experiment setting" allows to appropriately identify financing frictions by avoiding the endogeneity problems that arise when shocks to bank liquidity are due to changes in monetary policy, deposit growth or internal cash (Stein 2003).

Using monthly balance sheet information between 1998 and 2000 I find that lending indeed reacts to liquidity shocks and the magnitude of the response is quite large, in the order of \$0.7 per dollar of liquidity expansion. This result is more than twice the point estimate found using deposits as the exogenous shifter and it is in the same range of recent estimates of investment sensitivity to exogenous changes in cash flow at the firm level (Rauh 2004). I further show that in bank fixed effect specifications, the estimated loan sensitivity does not vary significantly across banks of different size or capitalization, dimensions used in previous literature to proxy for financial constraints.

Merging the bank level data with loan data from the public credit registry I can look at how liquidity shocks affect the default rate of loans and the characteristics of the average loan recipient. I find that the average loan default rate over all types of borrowers doesn't change when a bank faces a liquidity shock, which suggests banks are severely constrained. The results also indicate there are systematic variations in this result across borrowers with (*old*) and without (*new*) a preexisting credit relationship with the bank. For example, I find that when banks face a liquidity expansion they reduce collateral requirements on their loans to *new* borrowers and the default rate of these borrowers increases significantly. Banks do not, however, relax liquidity requirement to *old* borrowers. Instead, the past repayment performance of old borrowers drops when banks expand lending. These results suggest banks ration credit on different margins for the two types of borrowers.

I also find that the default rate for old borrowers does not increase during liquidity expansions, even though past repayment history is a strong predictor of default in the cross section. This suggests banks elicit information from their borrowers through the relationship that is relevant for predicting default. I confirm this by showing that lending to new borrowers with a credit history in other institutions faces a sharply increasing schedule of default risk, which is consistent with severe adverse selection.

The implications of the findings of this paper are twofold. First, a large loan-liquidity sensitivity means that the potential magnitude of the lending channel of monetary policy can be sizeable. Although the effects of liquidity on aggregate lending might be mitigated in general equilibrium by the lending response of unconstrained banks, the results here suggest that the adverse selection problems can be large enough to prevent this from happening. Second, the fact that financially constrained banks in this context may be lending sub-optimally suggests there are potentially important costs to capital and liquidity requirements. Regulation is necessary to prevent excessive risk shifting but the potential downside is that it may also inefficiently distort bank lending behavior. And both effects will be especially strong for smaller, bank dependent businesses for whom banking relationships matter the most.

The first section of the paper provides the institutional and theoretical framework of the rest of the paper and describes the data. Section 2 is devoted the estimation of the lending-liquidity sensitivity. It discusses previous work, the empirical specification, the identification strategy, and comments the results. Section 3 focuses on the relationship between liquidity and risk. Section 4 makes some final remarks about the results.

1. Background and Data

1.1. The Argentine Banking System in the 90s

The Argentine banking sector and regulatory system were thoroughly overhauled twice during the 1990s. The period following the hyperinflation spell that ended in 1990 was marked by the creation of an independent regulatory agency within the Central Bank, the abolition of the deposit insurance, and an increase of capital requirements above Basel. The 1992-1994 period was characterized by fast economic growth, sharp rises in assets prices and fast development of the financial system. But the Tequila crisis in 1995 provoked widespread bank panics that put in evidence the weaknesses of the regulation. The regulatory system was amended again to introduce a combination of market discipline and supervision. Amendments included the creation of a limited, fully funded deposit insurance; the replacement of reserve requirements with liquidity requirements, which decline with the residual maturity of each liability; the requirement of annual bank ratings provided by a rating agency registered with the Central Bank; mandatory bank subordinated liability of 2% of deposits each year; the creation of a Public Credit Registry to ease the monitoring and disclosure of the risk composition of bank assets and; the privatization of most government owned banks.

All the empirical results of this paper are estimated restricting the sample to the period that follows this second regulatory reform. The banking system in this period is characterized by rapid deposit growth (see Figure 1) and an important presence of foreign capital[1]. Another feature of the post reform banking sector was its imperviousness to large emerging market shocks (1997 Asian crisis, 1998 Russian moratorium and 1999 Brazil devaluation), which some authors have interpreted as evidence of the soundness of the new regulatory setup (Calomiris and Powell 2000). This setting of market incentives, information disclosure and liquidity growth stacks the cards against finding evidence of financial frictions in the banking system and thus is ideal for addressing the empirical questions posed in the introduction.

1.2. Program Characteristics

The Credit Program to Small and Medium Sized Firms (a.k.a. MYPES) was implemented in Argentina between 1993 and 1999 and provided financial intermediaries limited financing at a subsidized interest rate (average dollar deposit rate). The program was funded by the Inter-American Development Bank (IDB) and had the objective of increasing formal intermediary lending to small businesses. The MYPES falls into the category of what, in the development agency jargon, is known as an *on-banking* or a *two-step lending* program. The common feature of on-banking programs is to make financing available to existing financial intermediaries, with the condition that a proportional amount must be lent in turn to a narrowly defined group of borrowers. This type of credit market intervention is widely used in developing

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[1] By 1998 foreign-owned banks held 53% of the assets and 46% of the loans of the financial system.

countries: the IFC (World Bank) alone allocated during the last decade more resources to small firms through on-banking "than through any other individual program" (Barger 1998).

The MYPES required banks to issue \$1 of loans to eligible borrowers for every \$0.75 of program financing received[2]. Eligible borrowers were firms with less than 20 workers and less than \$200,000 in annual sales. In previous research (Paravisini 2003) I show that *eligible borrowers'* debt increased by less that 10 cents for every dollar of program financing received by participating banks. I also show that banks circumvented the allocation rule by picking the best performing borrowers among their eligible clients and re-labeling existing debt as "program loans". The conclusion there was that banks were largely unconstrained in their use program financing, which suits the purpose of this paper.

The MYPES program was small relative to the size of the financial system: it allocated around \$90 million among participating banks, which represented 0.1% of total loans in 1995. This implies that the program had a small impact on aggregate liquidity and was unlikely to influence interest rates, which allows focusing on the partial equilibrium effects of the liquidity expansion. On the other hand, the amount of financing was sizeable relative to banks that participated in the program: financing represented about 1.8% of stock and 10.6% of the flow of loans during the months of implementation.

Program financing was distributed in 12 waves between 1993 and 1999 (Table 1). The amount of resources allocated to each wave varied under the discretion of the IDB. The yearly flow of program financing is plotted in Figure 2. The plot displays two peaks: one during years 1995 and 1996 and another one in 1999. The first peak coincides with a period of massive deposit drains triggered by the Tequila crisis (see Figure 1) and with the subsequent regulatory reforms. The second peak was driven by an "administrative rush" to finish allocating the program resources before year 2000. According to MYPES managers, a second phase of the program (MYPES II) was planned to begin in 2000 and financing for this phase was conditional on the complete execution of the budget of the first one. I will take advantage of the fact that each wave of the program provides an independent shock to liquidity and perform estimations restricting the sample to the final waves. This avoids the potential bias that may arise from the program being purposely timed to provide liquidity to

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2 To avoid confusion between loans from the government to the banks and the associated loans from the banks to eligible firms, I will call loans to banks "program financing" and loans to firms "program loans to firms".

weaker banks when they most needed it. If, for example, banks used program resources to compensate for negative shocks in deposits, the resulting loan-liquidity sensitivity estimate would be biased downwards.

A month prior to the beginning of each wave, the Central Bank of Argentina announced publicly the amount to be distributed. Banks submitted an application to participate in the wave, which included the amount of financing required. If the sum of the requested financing of all applicants exceeded the amount of resources in the wave, financing was distributed among applicants according to a formula based on bank characteristics. The financing demand surpassed available resources in every wave, and the formula was used to allocate resources in each of them. The formula assigned a higher fraction of the wave resources to banks with a smaller average size of loans and a higher proportion of loans in poor provinces[3]. Each participating bank was assigned a point score according to these characteristics and the wave resources were allocated proportionally to each bank's score. The point score that corresponds to an average loan size and a regional distribution is described in Table 2 and Table 3 respectively. I will use this formula later to simulate the expected amount of available program financing to each bank in each wave. The simulated available financing will be uncorrelated with bank financing constraints or investment opportunities (beyond the observable characteristics included in the formula), and will be used as an exogenous shifter of bank liquidity.

Of the 126 financial institutions in the sample between 1995 and 2001 (see the data description in the next subsection), 29 received program financing at some time. The number of banks that participated in each wave varied between 5 and 15, and participation was positively correlated with the amount of resources to be distributed in each wave (see Figure 2). Asked about the participation choice, executives of participating banks acknowledged that although the program provided a cheap source of finance, the amount at

[3] Originally, the banks had to submit also in their application the fraction of matching resources the bank would commit to the ensuing loans to eligible firms and the interest rate they would charge on these loans. Both of these variables were to be included in the distribution formula if the requested financing exceeded the amount of resources in the wave. However these variables were dropped from the formula after the first two waves because there was no cross sectional variation in the bids. The matching funds bid was exactly the minimum matching funds required by the program ($1 for every $3 of program financing) in 98% of the cases. And the interest rate bid matched a "suggested" rate provided by the government. The difference between the highest and the lowest interest rate bid in any wave was at most 0.06 percentage points and zero 81% of the time. This variation was negligible relative to the average interest rate of 13.7% during the period.

stake was sometimes too small to compensate the administrative costs involved[4]. Since program participation was likely to be related to factors affecting the lending-liquidity sensitivity (e.g., negative deposit shocks, new investment opportunities) I will exploit changes in wave size as an exogenous source of variation in participation. The descriptive statistics of banks by their participation status show how the endogenous participation decision might produce biased estimates if unaccounted for (see Table 4). Participating banks are smaller than non-participating ones and thus are likely to have higher loan-liquidity sensitivities than non-participating ones. Thus, a comparison of participating versus non-participating banks could lead to an upward bias in the estimate of this sensitivity.

Finally, banks had three months to use the allocated resources or pay a penalty equal to twice the interest rate of the unused balance. The unused balance would be reassigned in the next wave of the program among the participating banks in that wave. Also, banks bore the credit risk of the loans to the eligible firms: repayment of program financing was not contingent on firm loan performance. However, the repayment schedule of the program financing matched exactly the schedule of the associated firm loan. The duration of loans to firms was limited to 36 months (plus 12 months of optional grace period). The descriptive statistics of the program loans to firms (Table 5) show that the median duration of program firm loans was 36 months and the median grace period was zero. This suggests banks also selected eligible firms in order to maximize the time they could hold program financing within the imposed constraint.

To summarize, the program provided banks with a limited amount of low cost, medium term financing. The cross sectional and time series variation of the *available* program financing and the probability of bank participation in the program can be simulated using wave size and timing and a cross sectional allocation rule which are independent of investment opportunities or deposit shocks. The simulated available financing can then be used as an exogenous shifter of bank liquidity to estimate the effects of liquidity shocks on the lending decision of banks. Next I discuss how financing frictions can affect the response of bank lending to the availability of new sources of subsidized finance.

[4] Participating banks had to provide the program administrators with a database containing the characteristics of the recipients of the loans associated with the program. They also had to send monthly reports of the repayment performance of these loans.

1.3. Financing Frictions and Lending Behavior

1.3.1. Loan-Liquidity Sensitivity

In a world without financing frictions the marginal return on investment on all projects will be equal (Modigliani and Miller 1958). Profit maximizing banks are able to raise any amount of finance at the market rate, r_m, and lend until this marginal cost of finance is equal to the marginal return on loans. If banks face a declining schedule of marginal loan profitability, lending beyond this point yields a return lower than r_m. If a bank in this world receives one dollar of subsidized financing (at a rate $r_s<r_m$), it will use it to repurchase a dollar debt and earn r_m-r_s. The alternative is to issue $1 in new loans, which would yield a return below r_m-r_s. Thus, an extra dollar of available cheap financing will not affect either total loanable funds (total financing minus reserve requirements) or lending of profit maximizing banks in a frictionless world, as long as banks hold some financing at the market rate.

In an alternative scenario with informational asymmetries and agency problems bank external financing is costly. Banks will be unable to raise unlimited amounts of financing at the market rate because issuing debt either is a bad signal of the quality of banks assets or increases the incentives of self-interested managers to engage in opportunistic behavior (Stiglitz and Weiss 1981; Myers and Majluf 1984; Jensen 1986). These frictions imply that the marginal cost of external financing is not constant at r_m, but increasing in the amount of externally raised finance. Banks will lend until the marginal cost of finance is equal to the marginal return on loans, but now a $1 of subsidized financing will shift out the marginal cost of external finance. When banks face financing frictions, an increase in available cheap finance leads to an expansion total bank loanable funds and in lending.

This discussion suggests a simple test for financial constraints in the context of the program described in the last subsection. A positive relationship between bank loanable funds and the availability of program financing when banks hold liabilities priced at the market rate (e.g. any bank liability other than deposits) can be taken as evidence of financing frictions. If this relationship exists, changes in the availability of program financing can be used as an exogenous shifter of bank liquidity to estimate the magnitude of the lending-liquidity sensitivity.

To put these ideas in a conceptual framework, I consider a version of Froot, Scharfstein and Stein (1993), Kaplan and Zingales (1997) and Stein (2003) reduced form two-period models that synthesize the costly-external-finance intuition for non-financial firms. This framework is intended to convey the intuition behind the empirical strategy that I will follow in the rest of the paper and not to explain optimal bank investment and financing decisions. Banks choose the amount of lending, *L*, and external financing, *e*, to maximize expected profits:

$$\max_{L,e} \frac{1+\lambda}{1+r} f(L) - (1+r_s)s - [1+r_m+\theta C(e)]e \tag{1-1}$$

$$\text{s.t. } L = s + e$$

where $f(L)$ is the expected gross return on loans and s represents subsidized finance and r is the discount rate. Also, r_m and r_s are the market and the subsidized price of external finance respectively. The cost of external financing, $r_m+\theta C(e)$, is equal to the market rate when there are no financing frictions ($\theta=0$), and increasing in the amount external funds [C'>0, C''>0] otherwise ($\theta>0$). Expected return on loans, *f( )*, is an increasing and concave function of lending due to, for example, an increasing and convex profile in the probability of default of potential borrowers. Finally, λ represents the potential private benefits managers derive from investment.

The level of lending that maximizes expected profits when there are no financing frictions, L^*, equates the market cost of financing and the PDV of the marginal expected return on loans:

$$\frac{1+\lambda}{1+r} f'(L^*) = 1 + r_m \tag{1-2}$$

as long as the amount of subsidy does not exceed L^* ($s \leq L^*$). In a frictionless world, an increase in the amount of subsidized financing will lead to a one for one reduction in external financing ($de^*/ds=-1$), and bank total funding and lending will be unchanged. This result is depicted in Figure 3.

On the other hand, if θ>0, lending will be given by the first order condition of the bank's program (1-1):

$$\frac{1+\lambda}{1+r} f'(\hat{L}) = 1 + r_m + \theta g(\hat{L}-s)$$

$$\text{with } g(\hat{L}-s) = C(\hat{L}-s) + (\hat{L}-s)C'(\hat{L}-s) \tag{1-3}$$

Since *g( )* is increasing and *f '( )* is decreasing, it follows that $d\hat{L}/ds > 0$. In words, total funding and lending are increasing in the amount of subsidized finance (see Figure 4). It is also easy to show that $d^2\hat{L}/dsd\theta > 0$, which implies that the sensitivity of lending to subsidized finance is increasing in the magnitude of the financing frictions. This result will be useful later to check whether the loan-liquidity sensitivity changes along observable proxies of financing constraints.

1.3.2. Two Views of Financing Frictions

Financing frictions affect the ability of banks to make loans and will spill over to their borrowers. These frictions may hinder the proper funding of otherwise profitable bank dependent firms. This is the result in Stein (1998), where bank lending is inefficiently low because of adverse selection costs in external financing. A stronger version of this *sub-optimal lending* view suggests financing constraints may even reduce the incentives of banks to monitor/screen borrowers, such that frictions not only reduce the amount of lending but may also increase the default risk for given borrower characteristics (Besanko and Kanatas 1996; Thakor 1996). Furthermore, constrained banks may be unwilling to supply relationship borrowers with liquidity when they face adverse shocks and cause premature termination of profitable projects (Detragiache, Garella and Guiso 2000). Under the sub-optimal lending view of financing frictions a liquidity expansion increases bank funding of positive NPV projects and might reduce the probability of default.

On the other hand, financing frictions may arise optimally to affect the lending behavior of banks. In models where there is tendency of managers to over-invest [$\lambda>0$ in (1-2)] available financing is endogenously determined to balance the ex post over- and under-investment distortions (Stulz 1990; Hart and Moore 1995). Also in a stronger version of this *optimal constraints* view, banks must be constrained in order to credibly commit to exert monitoring effort on their borrowers (Holmstrom and Tirole 1997). The optimal constraints view implies that an exogenous liquidity expansion will increase financing of unprofitable projects and increase the probability of loan default.

Testing whether the liquidity expansion leads to an increase in positive NPV lending requires loan level data on interest rates and monitoring/screening costs which is unavailable for this research. I will take instead an indirect approach by looking at how liquidity affects lending risk to test between the two "strong" views of financing constraints. The two views have contrasting and testable predictions about the effect of a lending expansion on loan risk. In the strong sub-optimal lending view, we expect that borrowers of similar observable characteristics are more likely to repay when lending expands. Thus, the change in the average default rate during liquidity expansions should be abnormally low, once the relevant observable borrower characteristics are accounted for. In fact, the starkest case for the sub-optimal lending view would occur when the default risk drops or doesn't change during liquidity expansions. But even when the default risk increases as a result of the liquidity expansion, I can test whether the increase is abnormally low using the appropriate benchmark. The availability of loan level data will allow estimating an approximate benchmark by looking at the conditional probability of default given observable borrower characteristics. For example, suppose that a 10 percentage point decrease in collateral requirements can be associated with a 5 percentage point increase in the probability of default in the universe of loans. Also, suppose banks reduce in 10 percentage points the collateral requirements on loans when they receive a liquidity shock and as a result the probability of default rises 1 percentage point. Then, the increase in default risk due to the liquidity expansion is too low given the drop in collateral requirements and the evidence would go against the optimal constraints view.

The analytical framework provided in section 1.3.1 can be used again to fix the intuitions conveyed here. The expected return on lending, $f(L)$, can be rewritten more generally as a function of the riskless gross return on loans, R, and probability of default of loans, p. This setup is chosen such that changes in the expected return on loans are driven exclusively by changes in the probability of default, and allow to abstract from loan pricing decision.[5] The probability of default is, in turn, an increasing and convex function of the average borrower quality, q:

$$f(L) = R\left[1 - p\left(q(L;X)\right)\right] \tag{1-4}$$

Average quality is an unobservable borrower characteristic that measures her ability or willingness to repay and depends on total lending, L, and on average *observable* borrower characteristics, X, in a way I discuss below. Given the assumptions so far, this setup already gives the rationale for the first version of the test: if the probability of default is not-increasing in lending, the bank must be lending sub-optimally. Put in other words, the optimal level of frictionless lending, L^*, will occur at a point where the probability of default is increasing in lending. Otherwise, it is possible to finance an expansion of lending at the constant cost r_m and increase profits. Intuitively, if $dp/dL \leq 0$ banks are operating in the flat

[5]As mentioned in the description of the program, the source of liquidity shocks used in this paper is unlikely to affect prices in the loan market.

portion of the marginal expected return curve in Figure 3, which implies they are inefficiently constrained.

Now consider a case where probability of default is increasing in lending. I exploit the fact that the strongest version each view of financing frictions predicts a different relationship between borrower quality and lending. The sub-optimal lending view suggests that expanding loans may reduce the vulnerability of bank dependent firms or be accompanied by an increase in the monitoring/screening effort of the bank[6], which tends to increase unobservable borrower quality (*q*) conditional on observable borrower characteristics (*X*). The optimal constraints view implies that an expansion in lending beyond the constrained level reduces monitoring incentives, which reduces borrower quality given *X*. Thus, the sign of the partial effect of lending on the probability of default (∂p/∂L) will provide information about the nature of the financing constraints. Paraphrasing in terms of the original intuition, in the strong version of the sub-optimal lending view of financing frictions, ∂p/∂L will be negative and the liquidity shock will induce an increase in the default rate that is too low when the borrower characteristics are taken into account.

Formally, the total differential of the probability of default is given by:

$$dp = \frac{\partial p}{\partial X} dX + \frac{\partial p}{\partial L} dL \tag{1-5}$$

Dividing by *dL* and rearranging, the expression for ∂p/∂L is:

$$\frac{\partial p}{\partial L} = \frac{dp}{dL} - \frac{\partial p}{\partial X}\frac{dX}{dL} \tag{1-6}$$

The first term on the right hand side is the total change in the probability of default with respect to a change in lending. In the empirical setting this corresponds to the estimation of the effect of the liquidity expansion on the probability of default. The last term, *dX*/*dL*, is the effect of a change in lending on observable borrower characteristics. This term is expected to be negative since banks will in general relax their screening criteria (e.g. lowering the cutoff credit score) in order to expand lending. This can be estimated by looking at how the average characteristics of loan recipients change with the expansion of liquidity. The second term represents the partial effect of borrower characteristics on the probability of default. As borrowers with worse observable characteristics are more likely to default this

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[6] This could come from introducing explicitly the monitoring effort and lending as complements in the function of the probability of default.

term is also expected to be negative. I will approximate this partial effect by estimating a linear probability model of default on borrower characteristics in the universe of loans.

The observable borrower characteristics that will be used as predictors of the probability of default are the collateral to loan ratio and a measure of past repayment performance of loan recipients. Higher collateral increases the contingency of the loan contract and should elicit a higher effort from the borrower, leading to a lower probability of default. Better past performance is a positive signal of the ability of the entrepreneur or of the quality of the project and should also predict a lower probability of default.

1.4. Data Sources

This paper uses three sources of data. First, detailed information on balance sheets and monthly earnings reports for all the banks in the Argentine financial system between 1995 and 2001 from the Central Bank of Argentina. As I argued in the description of the program, the preferred estimates will be based on the 1998-2000 sub-sample, when the final waves of the program took place.

The second source of data is the Public Credit Registry database, or CDSF for its acronym in Spanish (Central de Deudores del Sistema Financiero). Each observation in this database represents a loan i held by firm j with bank k at month t. It containts monthly data on all loans held by firms or individuals with more than $50 of debt with a financial institution in Argentina. The CDSF is available for all borrowers after January 1998.[7] For each credit and each month, the data available are: the name of the debtor, the name of the bank, the principal withstanding, the amount of collateral posted and a code describing the debt situation. This code has six categories from 1 to 6 where 1 represents a good standing loan and 5-6 represents unrecoverable loans. The categories are precisely defined in terms of the days behind in payment, debt refinancing and bankruptcy filings (Gutiérrez-Girault 2002).[8,9]

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[7] The collection of this data started in early 1996. However, the accounts of what information was available before 1998 and when are contradictory. See for example Escudé et. al. (2001) and Fakenheim, M. and A. Powell (2003). However, all research conducted by the BCRA and others using the CDSF only includes post 1998 data.

[8] Situation 1 (normal): all payments on time. Situation 2 (with potential risk): small and occasional delays in repayment. Situation 3 (with problems): delays in repayment between 90 and 180 days. Repays accrued interest but requires principal refinancing. Situation 4 (high insolvency risk): repayment delays between 180 and 360 days, bankruptcy filings for more than 5% of the firm's equity, has principal and interest refinancing requiring principal condoning, the bank received payments in kind. Situation 5 (unrecoverable): bankruptcy declared. Situation 6 (unrecoverable by technical disposition): late repayments of more than 180 days with intervened financial institutions.

[9] The bank descriptive statistics in Table 4 are calculated using the balance sheet and CDSF databases.

It is important to note a feature of the CDSF related to the information reported about credit lines and credit cards. Since the bureau was created for regulatory reasons to measure bank asset risk, credit limits and not actual amounts of credit outstanding are reported. That is, if a firm opens a credit line for up to \$100,000 with a bank, then the CDSF will show a loan of \$100,000 for every month the line is available regardless of the actual amount borrowed. This feature is actually an advantage in our application since the outcome of interest is the availability of credit.

A third source of data is the program database, collected and managed by the Ministry of Economy in Argentina. This database has detailed characteristics about firms that received loans from the program, such as characteristics of the loan (date of initiation, principal, duration, grace period, amount of each payment, grace period, interest rate), characteristics of the firm (number of workers, annual sales), and name of the intermediary bank that made the loan.[10] The program database and the CDSF could be linked using a unique tax identification code (CUIT).

2. Measuring the Lending-Liquidity Sensitivity

2.1. Empirical Specification and Previous Research

The usual specification used in the literature that looks at the bank lending-liquidity sensitivity estimates the direct relationship between loan growth and a measure of changes in the availability of cheap financing, typically given by changes in monetary policy (Bernanke and Gertler 1995; Hubbard 1995; Kashiap and Stein 2000; Kishan and Opiela 2000), deposit growth (Jayaratne and Morgan 2000; Ashcraft 2003) or internal cash (Ostergaard 2001):

$$L_{i,t} = \alpha_i + \alpha_t + \beta D_{i,t} + \gamma X_{i,t} + \varepsilon_{i,t} \tag{2-1}$$

where $L_{i,t}$ is loan growth of bank i at month t, $D_{i,t}$ represents a measure of the liquidity shifter, α_i and α_t are bank and month fixed effects, $X_{i,t}$ is a set of controls and $\varepsilon_{i,t}$ is the error term. The main caveat in this literature is that the liquidity shifters are likely to be correlated with loan demand and lead to a biased estimation of β in (2-1). For example, an increase in deposits or in internal cash may signal better future lending prospects of the bank and will be correlated with loans even in the absence of financing constraints. This problem has been approached in several ways. First, by introducing a measure of investment opportunities

[10] The firm program loan descriptive statistics shown in Table 5 are calculated using the program database.

among the controls (e.g. Tobin's q, level of economic activity). Second, by looking at the differences in the lending-liquidity sensitivity across banks that are more likely to face financing constraints according to observable characteristics (e.g. smaller, less capitalized banks). Both of these approaches are also used in the early literature on the investment-cash flow sensitivity and have been criticized from empirical and theoretical grounds. Poterba (1988) and Erickson and Whited (2000) suggest the observed correlation between investment and cash flow can be entirely driven by measurement errors in q. Furthermore, the cross sectional variations in the investment-cash flow sensitivity appear in the data even for firms that are not financially constrained (Kaplan and Zingales 1997; 2000), and can be predicted from models without financing frictions (Alti 2003). The third and most convincing approach is to look at the lending-liquidity sensitivity in a "natural experiment" setting, in which the shock to the financial position of the bank is independent of its investment opportunities (Stein 2003). The only example of this approach in the banking context is by Peek and Rosengren (1997; 2000) who show how lending by US branches of Japanese banks declines when the stock price of these banks drops.

I use the "natural experiment" approach in this paper by exploiting the expansion of available financing provided by the government program as the source of variation in bank liquidity. I will estimate the relationship between loan growth and liquidity as in (2-1), with liquidity measured as the growth of the bank loanable funds, F:

$$L_{i,t} = \alpha_i + \alpha_t + \beta F_{i,t} + \varepsilon_{i,t} \tag{2-2}$$

Loanable funds are the sum of equity, deposits and other liabilities, minus reserve requirements. Growth refers to the proportional growth rate, calculated as the change in the log of the variable[11]. I will use changes in the simulated *availability* of program finance, $\hat{E}$, as an instrument for F and estimate β in (2-2) by 2SLS. Section 2.2 discusses in detail how the availability of program finance is simulated using the predicted probability of participation. The estimated β_{2SLS} will be the elasticity of lending to changes in liquidity. The first stage of this estimation represents the effect of the expansion in the simulated available financing on bank liquidity:

$$F_{i,t} = \alpha_i + \alpha_t + \varphi \hat{E}_{i,t} + \eta_{i,t} \tag{2-3}$$

[11] That is, $\ln(X_t)-\ln(X_{t-1}) \approx (X_t - X_{t-1})/ X_{t-1}$ when $X_t - X_{t-1}$ is small.

The discussion in section 1.3.1 concluded that a positive estimation of the sensitivity of liquidity to available finance, φ, will occur only if banks face financing constraints.

Apart from dealing with the endogeneity problem discussed before, this setting has the distinctive advantage that the size of the liquidity shock is observable. While Peek and Rosengren provide an estimate of the change in lending due to a one percentage point decline in the parent bank's risk-based capital ratio, I will provide an estimate of the change in lending per dollar change in liquidity, which is easier to interpret. But more importantly, I can compare the 2SLS results with estimates based on deposits and internal cash as an instrument for liquidity. This will allow me to assess the magnitude and direction of the bias of previous results, which is a priori ambiguous (Rauh 2004). Furthermore, I can verify whether the loan-liquidity sensitivity varies across observable measures of financing frictions by estimating the following specifications:

$$L_{i,t} = \alpha_i + \alpha_t + \beta F_{i,t} + \beta' F_{i,t} \times DumSmall_i + \varepsilon_{i,t} \quad (2\text{-}4)$$

$$L_{i,t} = \alpha_i + \alpha_t + \beta F_{i,t} + \beta' F_{i,t} \times DumLowCap_i + \varepsilon_{i,t} \quad (2\text{-}5)$$

Here the liquidity measure is interacted with a dummy equal to one if the bank is in the lowest 20% of the assets distribution (2-4), and equal to one when in the lowest 20% of the equity to capital ratio (2-5). The instruments in each of these specifications are the expansion in available finance as before, and also the interaction between the available finance and the DumSmall and DumLowCap dummies respectively. The coefficient on the interaction term, β', will be positive if smaller and low capitalized banks indeed have a higher lending-liquidity sensitivity than other banks.

2.2. Dealing with Endogenous Program Financing

The key assumption in the previous empirical strategy is that program financing affects bank liquidity in a way uncorrelated with investment opportunities, deposit shocks or other factors that affect either liquidity or the decision to lend. As the description of the program in Section 1.2 suggested, *actual* program participation and available financing were likely to be correlated with these factors. This section describes how the potential endogeneity in participation and financing are dealt with using the time series variation of wave size and the cross sectional allocation rule of the program.

2.2.1. Predicted Probability of Participation

Bank executives commented that when the amount of resources in a program wave was small, the potential funding from the program was too low to justify the costs of participating. Since potential funding was driven by exogenous variables, like wave size and the point scores each bank received according to loan size and regional loan distribution, I will be able to predict bank participation based solely on variables that were uncorrelated with the lending decision.

Specifically, the participation choice can be modeled by assuming bank *i* participates in program wave *w* only if the potential financing that can be obtained from participation exceeds a bank and wave specific parameter $\eta_{i,w}$. Potential financing, h(.), is a function of wave size, A_w, and the point score bank i obtains according to its average loan size ($Zsize_{i,w}$) and regional loan distribution ($Zregion_{i,w}$) from Table 2 and Table 3 respectively. For now I assume an arbitrary functional form for potential financing. In particular, I choose a second-degree polynomial on wave size and the point scores:

$$h(A_w, Zsize_{i,w}, Zregion_{i,w}) = \sum_{s}^{3}\sum_{u}^{3}\sum_{v}^{3} \xi_{s,u,v} A_w^{s} Zsize_{i,w}^{u} Zregion_{i,w}^{v} \tag{2-6}$$

Assuming $\eta_{i,w}$ is normally distributed, the probability that bank *i* participates in wave *w*, $p_{i,w}$, is given by:

$$p_{i,w} = \Pr(h(A_w, Zsize_{i,w}, Zregion_{i,w}) > \eta_{i,w}) \tag{2-7}$$

The parameters of this participation model can be estimated using maximum likelihood (probit) and used to obtain a predicted probability of participation, $\hat{p}_{i,w}$. It is possible that banks tried to game the resource allocation formula by manipulating the loan size and distribution to increase their share of program resources. To avoid introducing this source of bias in the estimation of the probability of participation, I don't allow the region and size point scores to vary by wave. Instead I use the scores corresponding to the first time the banks are observed in the sample. This is, the following probit specification is estimated:

$$p_{i,w} = \Pr(h(A_w, Zsize_i, Zregion_i) > \eta_{i,w}) \tag{2-8}$$

where the variation in participation across waves and across banks are given by the interaction between wave size and initial bank characteristics. To see how close predicted participation fits actual participation, Figure 5 plots the actual and the predicted number of bank participations by year[12]. The plot shows that the predicted participation series tracks the actual one quite well.

2.2.2. *Simulated Availability of Program Financing*

When a bank participates in a wave, the amount of program finance it will receive depends on the amount of resources in the wave and the number and characteristics of all the participating banks in that wave. The program rules stipulated that each bank would receive a fraction of the resources available in the wave that was proportional to the ratio of their score points relative to the sum of the scores of all participating banks. This allocation rule can be summarized in the following formula:

$$E_{i,w} = A_w \left[\frac{Zregion_{i,w}}{2 \cdot \sum_{j}^{n_w} Zregion_{j,w}} + \frac{Zsize_{i,w}}{2 \cdot \sum_{j}^{n_w} Zsize_{j,w}} \right] \tag{2-9}$$

$E_{i,w}$ is the *actual* amount of financing bank *i* receives from the program when it participates in wave *w*, and is a function of wave size, A_w, bank i's point scores, $Zsize_{i,w}$ and $Zregion_{i,w}$, the number of participants in the wave, n_w, and the sum of all participants' point scores. The previous discussion suggests the number and characteristics of participants in each wave in endogenous. The predicted probability of participation from the previous subsection can be used to estimate the expected sum of the characteristics of program participants. This is done by summing the bank characteristics of all banks (participating and non-participating) weighted by the predicted probability of participation ($\hat{p}_{i,w}$). Using this expected sum in (2-9) I simulate the amount of program financing bank *i* would have received if it had participated in wave *w*:

$$\hat{E}_{i,w} = A_w \left[\frac{Zregion_i}{2 \cdot \sum_{j}^{N} \hat{p}_{j,w} Zregion_j} + \frac{Zsize_i}{2 \cdot \sum_{j}^{N} \hat{p}_{j,w} Zsize_j} \right] \tag{2-10}$$

where the region and size point scores of each bank are taken when first observed in the sample to avoid the rule gaming bias discussed before. Equation (2-10) gives us the expected

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[12] The predicted number of participants in a wave is just the sum of the predicted probabilities of participation across all banks. If the same bank participates in two waves during a year it counts as two participations for the graph.

increase in the availability of program financing of bank *i* at wave *w*. To calculate the changes in available financing by month ($\hat{E}_{i,t}$) I assume, first, that banks drew the available finance in three equal parts during the months following the date a wave begins; and second, that the program financing was repaid in 36 equal monthly parts after being received. The first assumption follows since banks had three months to draw the resources from the credit line in the Central Bank without penalty. The second assumption attaches to program financing the same repayment schedule of the median firm loan as described in Table 5.

In the last two lines of Table 4 show the descriptive statistics of the resulting available financing variable (in levels and as a proportion of loans outstanding) by bank participation status. Available financing represents about 7.6% of loans during the sample period.

2.2.3. Identification Checks

It is necessary to check whether the simulated available financing variable is correlated with the actual program financing received by the banks. The bottom panel of Figure 6 shows that the actual and simulated stocks of available financing track each other well in the time series. A regression version of this comparison, which also accounts for the cross sectional variations in financing, implies estimating the following regression of the growth of actual financing on the growth of simulated financing:

$$E_{i,t} = \alpha_i + \alpha_t + \varphi' \hat{E}_{i,t} + \eta'_{i,t} \qquad (2\text{-}11)$$

The estimated parameters with and without the bank and month fixed effects are shown on columns 1 and 2 of Table 6. The estimations show a strong and positive correlation between the simulated and the actual financing, which is robust to the inclusion of bank and month dummies. Since actual financing growth can only be calculated when bank i held a positive amount of program financing at t-1, I run the same regression but using a dummy equal to one if bank *i* received some program financing at month *t* as the dependent variable. The results restricting the sample to program banks and using all banks are shown in columns 3 and 4 of Table 6. The estimates indicate that the simulated financing variable is a good predictor of bank participation in the program both within the program bank sample and in the entire bank sample.

And finally I revisit one of the key identification assumptions mentioned at the beginning of this section: that the simulated financing expansion should not be correlated with other shocks to liquidity. For example, banks may have applied for program financing when they faced unexpected deposit declines, in which case changes in program financing and past changes in deposits would be correlated. I estimate a regression of actual and simulated program financing on four lags of deposits and the results are shown in Table 7. Column 1 shows that actual financing was in fact negatively and significantly correlated with lagged shocks to deposits (2 and 4 lags). However, columns 2 and 3 show that simulated financing is not. This evidence shows how the simulated financing variable rids of the potential endogenous correlation that might be present in the actual financing variable.

2.3. First Stage: the Effect of a Credit Expansion on Loanable Funds

The discussion in Section 1.3 about the effects of financing frictions on lending behavior led to the conclusion that a change in the availability of cheap financing will affect bank liquidity only when banks are constrained. The relationship between available financing and liquidity is embodied in the first stage regression (2-3). A positive relationship between the available finance growth and liquidity (loanable fund growth), φ, would be consistent with financing constraints. Table 8 shows the estimated parameters of the first stage. There is a positive and significant relationship between credit expansion growth and bank liquidity both in the program bank sample (Column 1) and in the universe of banks (Column 2). The relationship is weaker in the entire bank sample as expected, since the financing expansion should have no significant effect on non-program banks. I check this in column 3, that reports the relationship between liquidity and financing expansion for the sample of banks that never participated in the program. The relationship is statistically insignificant.

This discussion suggests a graphical version of the first stage estimates. Program bank loanable funds should increase relative to those of non-program banks when the available financing increases. To check this is the case, the top panel of Figure 6 shows the ratio between the loanable funds of program and non-program banks. The ratio increases together with available program financing, plotted in the bottom panel. This indicates that the liquidity of participating banks increases relative to that of not participating ones when available program financing is expanding.

The results taken together suggest that the expansion of available cheap financing provided by the program affected bank liquidity. The fact that the simulated financing expansion is driven only by exogenous sources of variation, assures that the expansion in liquidity is not driven by other confounding factors that affect either liquidity directly or the demand for loans. Thus, the evidence is supports the hypothesis that banks face financing frictions. The next step is to explore the relationship between bank liquidity and lending of constrained banks.

2.4. 2SLS Estimation: The Lending-Liquidity Sensitivity

This section uses specification (2-2) to obtain the 2SLS estimate of the lending–liquidity sensitivity, β, using the expansion of available financing as a liquidity shifter. All the results that follow are estimated using the entire sample of banks. Table 9 shows the OLS and the 2SLS estimation results of β. The preferred estimate of the lending-liquidity sensitivity is 0.745 (column 3), obtained from restricting the sample to the final waves of the program. Considering that the average loans in the sample are $536 million and average loanable funds $616 million, the estimated elasticity implies that loans increase by $0.65 for every dollar of liquidity expansion. The estimate of the loan-liquidity sensitivity is lower (0.481) when all the waves of the program are used in the sample. Recall that the initial waves of the program coincided with massive deposit drains from the banking system. A negative bias in the loan-liquidity estimate during this period would result if the fall in deposits of program banks was relatively larger than for the rest of the banks. The rest of the results in the paper will be estimated using the restricted sample.

In order to compare the results with the previous literature I repeat the estimations using deposits as the sources of variation in liquidity. The resulting estimate of the loan-liquidity sensitivity is 0.361 (bottom panel of Table 9) which is heavily biased downwards. This result parallels that or Rauh (2004) who finds a similar downward bias in the estimates of the investment-cash flow sensitivity for a large sample of firms in the US.

Finally, I estimate the lending-liquidity sensitivity across banks of different size and capitalization using specifications (2-4) and (2-5). The coefficient of interest in this specification is the interaction term, β', which will be positive if banks in the lowest quintile of the asset or capitalization distribution have a higher lending-liquidity sensitivity[13]. Both point estimates are positive, but neither of them is statistically significant (Columns 2 and 3 of Table 10). These results hint at the potential bias that may result when identifying financing constraints relying on cross sectional variations in the lending-liquidity sensitivity. The magnitude of the cross sectional variation may be very small in proportion to the actual

[13] Of the program banks in the reduced sample, 40.7% are classified as small and 25.9% as low capitalized. Of the non-program banks, 51.0% are classified as small and 14.9% as low capitalized...

level of this sensitivity, and might lead again to underestimate the importance of the effect of financing friction on bank lending.

Summarizing the finding of this section, an increase in available financing produces an increase in bank liquidity that is consistent with the existence of financing frictions. The lending-liquidity sensitivity that results from these frictions can have a substantial magnitude and is potentially underestimated by previous research. I now turn to analyze the effects of financing constraints on bank lending behavior, and in particular on lending risk.

3. Liquidity and Lending Risk

3.1. Specifications with Loan Level Data

The following reduced form version of (2-2) is used to estimate the change in bank loan default risk and average borrower characteristics due to a liquidity expansion:

$$Y_{i,j,t} = \alpha_i + \alpha_t + \alpha_s + \varphi DumExp_{i,t} + \omega_{i,t} \tag{3-1}$$

Every observation represents a loan j given by bank i at month t. The left hand side variable is a measure of loan default or borrower characteristics. Loan default is measured as a dummy equal to one when a loan issued at time t has defaulted by time t+12. I also look at defaults at t+24 to check for potential changes in the timing of defaults. As mentioned previously, I use loan collateralization and loan recipient past performance as measures of observable borrower quality. Collateralization is the ratio of collateral to the amount of loan j. Past performance is measured as a dummy equal to one if the recipient of loan j has any non-performing debt between t-1 and t-12.

The variable of interest on the right hand side is $DumExp_{i,t}$, a dummy equal to one when bank i faces an expansion of program financing at month t. Financing expansion months are defined as the three months following the date a program wave begins. I instrument this variable with the predicted probability of program participation, described in section 2.2. The estimated φ can be interpreted as the change in the average of the dependent variable (averaged over bank-month cells) that results from a liquidity expansion. For example, assume (3-1) is estimated using the default at t+12 dummy as the dependent variable and we obtain φ=0.05. This result indicates the fraction of loans issued by a bank that defaults after 12 months increases by 5 percentage points when the bank receives a liquidity expansion. The rest of the right hand side variables are α_i and α_t, bank and month dummies as in (2-2), and α_s, an industry dummy. The industry dummy allows controlling for potential changes in the industry composition of the loan portfolio of the banks. Finally, ω is the error term.

The estimated φ using the default dummy as the dependent variable will be the measure of dp/dL in (1-6), or the effect of an expansion in lending on the probability of default. Similarly, using collateralization and past performance will provide estimates of dX/dL, or hao average borrower characterstics change as a result of a lending expansion. The partial effects of observable borrower characteristics on default, $\partial p/\partial X$, are approximated by estimating the following regression over all the loans j:

$$\text{DumDef}_{i,j,t} = \alpha_i + \alpha_t + \alpha_s + \zeta_1\text{DumPast}_{i,t} + \zeta_2\text{Collat}_{i,t} + \nu_{i,t} \qquad (3\text{-}2)$$

This is a linear probability model of default using past performance and collateral as dependent variables.

The descriptive statistics of the loans issued during the sample period are shown in Table 11. Of the 750,526 loans in the sample, 130,201 were issued to *new* borrowers, or borrowers without a previous relationship with the bank. On average, 12.2% of the value of the loan was covered by some type of collateral, 12.2% of the loans is non-performing after 12 months and 16.8% is non performing after 24 months. Loans to new borrowers are less collateralized and are more likely to default than loans to old borrowers (borrowers with a pre-existing relationship with the bank). Old borrowers have on average $58,550 of debt outstanding when received the loan and 14.1% of loan recipients hold some non-performing debt at the moment of receiving the loan.

3.2. Default Rate Results

The effect of the liquidity expansion on loan default risk can be characterized by estimating specification (3-1) using the default dummies as the dependent variable. The results of this estimation for the 12 month and the 24 month default dummy and for various sample are shown in Table 12. The coefficient of interest can be interpreted as the change in the proportion of loans that default due to a liquidity expansion. The point estimates for the entire sample of loans are negative but insignificant for both the 12 and the 24 month measures (columns 1 and 2 of panel 1). This implies that the liquidity expansion doesn't change in a statistically significant way the default risk of bank loans, which suggests banks are lending at a point where the schedule of loan risk is not sharply declining on average.

The second panel of Table 1 shows the results for the sample of new borrowers (borrowers without a previous relationship with the bank). Results in this subsample show a different picture: the 12-month default rate for new borrowers increases by 3.8 percentage points due to the liquidity expansion. The 24-month default rate is also positive but insignificant. Expanding lending to new borrowers does imply an important increase in loan risk. And the time profile of the default rate suggests that loans to new borrowers given during liquidity expansion also tend to default earlier. The results for the sample of old borrowers, shown in panel 3 of Table 12, follow the same pattern of the results for the entire sample. The changes in the default rate due to the liquidity expansion are negative but insignificant.

The analytical discussion in 1.3.2 suggests that these findings go against the optimal constraints view of financing frictions. Expanding lending does not entail on average an increase in loan default, which means that more lending could potentially increase profits if banks were not facing an upward sloping marginal cost due to financing frictions. From the borrower perspective, these results also indicate that financing constraints at the bank level may result in credit rationing of viable projects, although this is not necessarily true in the case of new borrowers.

3.3. Collateral and Past Performance Results

In general, it is likely that banks must lend to borrowers of an observable lower quality in order to expand lending. But finding that the default rate doesn't increase significantly when lending is expanded may suggest this is not the case. The previous finding would be consistent with banks having a large pool of rationed, observationally equivalent, positive NPV projects to choose from. But it would also be consistent with banks allocating loans at random. To look at this issue, I estimate the effect of the liquidity expansion on two observable borrower characterstics that are likely to be related to default risk: collateral and past performance.

Specification (3-1) is estimated using the collateral to loan ratio as the dependent variable and the results are shown in column 1 of Table 13. The estimate using the entire sample of loans (panel 1) indicates that the collateral to loan ratio fell by one percentage point due to the liquidity expansion and this change is significant. The fact that the marginal borrower of the bank has a lower collateral than the average borrower is consistent with banks rationing borrowers according to collateral. The result supports the hypothesis that banks lend to lower quality borrowers when liquidity expands.

The estimates for the new and old borrower samples (panels 2 and 3 respectively) suggest that the drop in collateral requirements comes entirely from lending to new borrowers. The collateral to loan ration of loans to new borrowers drops by 3.4 percentage points during liquidity expansions. Thus, the result regarding collateral could potentially explain the observed patterns in the sensitivity of the default rate to liquidity. If loan collateralization is a good predictor of default and banks are able to expand lending to old borrowers without relaxing collateral requirements, then it is to be expected that the default rate of old borrowers doesn't react to liquidity expansions.

But this brings out the question of how and why are then old borrowers rationed. I turn next to past repayment performance and estimate specification (3-1) again using as the dependent variable a dummy equal to one if the loan recipient has some non-performing debt outstanding at the moment it receives the loan. The result in column 2 of Table 13, which uses the sub-sample of old borrowers, shows that the fraction of loans issued to borrowers with non-performing debt increased by 4.7 percentage points during liquidity expansions. This result indicates that banks relaxed their lending criteria based on past performance during liquidity expansions, but that this did not result in an increase in the default rate of old borrowers. The findings regarding old borrowers are consistent with the sub-optimal lending view of financing constraints. But this result would also arise if past performance were a bad predictor of default.

The interpretation of the results presented so far thus relies on how good collateral and past performance are in predicting loan default. I analyze this issue by estimating specification (3-2) using a linear probability and a probit specification for the probability of default on collateral and past performance (columns 1 and 2 of Table 14). The results show a significant relationship between both collateral and past performance on the probability of default of a loan. A 10 percentage point decrease in the collateral to loan ratio can be associated with 0.5 percentage point increase in the probability of default in the entire sample, a 1 percentage point increase in the new borrower sample and a 0.35 percentage point increase in the old borrower sample. Also, a loan recipient that holds non-performing debt is 54% more likely to default than one with a clean slate. These relationships corroborate the previous conclusions.

3.4. Analysis

Section 1.3.2 suggested that the estimate in this section could be used to draw inferences about the way financing frictions affect lending behavior and risk. Under the strong version of the sub-optimal lending view of financing frictions, a liquidity expansion would lead to an abnormally low increase in default risk after taking into account observable borrower characteristics. The results regarding old borrowers seem to be consistent with this view. The liquidity expansion implied approximately a 5 percentage point increase in the fraction of lending to borrowers with non-performing debt. According to the estimated default-past performance sensitivity, this should have led to a 2.5 percentage point increase in the probability of default. However, there is no significant change in the probability of default of old borrowers during liquidity expansions, and the point estimate is actually negative. This result may arise if lending and monitoring are complements, such that banks increased the monitoring/screening effort as a result of the expansion. Another possibility is that the availability of credit to firms directly affects the probability of default, for example, by reducing the vulnerability to temporary liquidity shocks.

The new borrower case, on the contrary, does not conform to this story. The liquidity expansion implied a 3.4 percentage point decrease in the collateral to loan ratio of new borrowers. The estimated default-collateral sensitivity implies that this decline should lead to a 0.34 percentage point increase in the default rate due to the expansion. Although the actual increase in the default rate seems too high in the short run, this result is consistent when looking at the default rate after 24 months.

The systematic differences between the results for new and old borrowers suggest an alternative interpretation of the results based on banking relationships. Bank-borrower interactions may elicit *soft* information about borrowers (unobservable to the researcher) which is then used to allocate credit during liquidity expansions. This means that the analysis in the previous section would over-estimate the decrease in the quality of the borrowers during liquidity expansions. This interpretation doesn't change the fact that banks are able to expand lending without increasing default risk substantially, and suggests bank relationships are valuable in the sense that the allow banks to discern the good projects among ex ante observationally equivalent borrowers. On the contrary, lending to new borrowers has to be decided exclusively on observable characteristics that are related to default.

To inquire further into this issue I repeat all the previous estimations for the sample of loans to new borrowers that had a previous credit history with other financial institutions. If bank relationships don't matter and credit history does, the results for this group of borrowers should not be different from those of old borrowers. On the other hand, if banks obtain information through relationships that is unobserved by other financial institutions, then lending to new borrowers that have switched from other institutions will be subject to adverse selection.

The results for the sub-sample of new borrowers with a credit history are shown in panel 4 of tables 12 through 14. First note that only 4% of the loans new borrowers are issued to borrowers with a credit history. This fact alone might indicate bank reluctance to lend to this class of borrowers. Second, the default rate of loans to these borrowers increases by 17 percentage points during liquidity expansions (Table 12), which is consistent with a steeply increasing risk schedule. Furthermore, the results regarding collateral and past performance indicate that new borrowers with a credit history are rationed by both margins, unlike old borrowers who were rationed only by past performance. And finally, the relationship in the cross section between loan collateral and the probability of default for these borrowers is as large as for new borrowers. These results are consistent with the hypothesis that bank relationships matter and with severe adverse selection in the new borrower market.

4. Final Remarks

This paper sheds some light in the role collateral and credit ratings based on past performance play in the access to bank credit. Collateral has always played a central role in the analysis of the access to credit, or the lack thereof. Collateral can reduce the incentives of entrepreneurs to misbehave and can be used as a signaling device when banks are unsure of the firms' prospects. But in practice collateral is not a panacea. The relevant value of collateral is the value when the firm is in trouble, which is not only difficult to predict ex-ante, but also endogenous to the firm's decisions and subject to moral hazard itself. The results in this paper suggest that past repayment performance is a far better predictor of default than collateral, and that it is actually used more actively by banks as a credit rationing device once a credit history of the borrower is available.

On the other hand, results also indicated that past mistakes are over-weighted in the cross section, and that banks learn relevant information from their borrowers through relationships. Unsophisticated lenders that rely on cross sectional information, like the one provided by the public credit registry in Argentina, may punish past mistakes too harshly and precipitate foreclosure of perfectly viable borrowers. Noisy public signals about borrower quality might lead to an increase in the overall entrepreneurial risk and have ambiguous welfare implications. This is an open question both theoretically (Morris and Shin 2001; Angeletos and Pavan 2004) and empirically and deserves the attention of future research.

Finally, the possibility that the link between available collateral and access to credit can be relaxed has appealing policy implications: policies designed to jumpstart borrower-lender relationships and then back off can be effective enhancing the access to credit of particularly constrained businesses. This is exactly the intuition behind the design of on-lending programs like the one described in this paper.

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6. Tables

Table 1: Wave Distribution by Year

Year	Wave number
1993	1-2
1994	3
1995	4-5
1996	6-7
1997	8
1998	9
1999	10-11-12

Table 2: Allocation Formula Score Point According to the Average Size of Loan

Average size of loan		
From ($)	To ($)	Points
0	3000	100
3000	6000	97
6000	9000	94
9000	12000	91
12000	15000	88
15000	18000	85
18000	21000	82
21000	24000	79
24000	27000	76
27000	30000	73
30000	33000	70
33000	36000	67
36000	39000	64
39000	42000	61
42000	45000	58
45000	48000	55
48000	50000	52
50000	100000	30
100000	200000	20
200000	∞	10

Table 3: Allocation Formula Score Point According to Regional Distribution of Credits

Provinces	Points
Capital Federal, La Pampa y Santa Cruz	30
Gran Buenos Aires, Buenos Aires (Resto), Santa Fe, Córdoba, Mendoza, Entre Ríos, Neuquén, Río Negro, San Juan, San Luis, Tierra del Fuego y La Rioja	70
Formosa, Catamarca, Santiago del Estero, Chaco, Jujuy, Misiones, Corrientes, Salta, Chubut y Tucumán	100

Table 4: Bank Descriptive Statistics, by Program Participation (Thousands of $)

	All banks		Program banks		Non-program banks	
Variable	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Assets	1,095,287	2,396,431	543,985	599,719	1,244,598	2,667,256
Loans	536,344	1,241,008	283,790	332,044	604,744	1,382,174
Liabilities	979,350	2,168,293	488,200	539,852	1,112,370	2,414,047
Deposits	569,590	1,331,549	361,719	407,961	625,888	1,483,052
Loanable funds	616,099	1,348,276	382,853	418,375	680,614	1,503,195
Loans/Assets	0.500	0.146	0.500	0.109	0.485	0.199
Deposits/Assets	0.515	0.194	0.626	0.124	0.485	0.199
Equity/Assets	0.133	0.135	0.133	0.130	0.133	0.137
ROA	0.31%	1.22	0.14%	1.12	0.35%	1.24
Financial Rev./Loans (%)	13.6%	7.2	12.8%	2.4	13.9%	8.0
Simulated financing	1,547.5	494.9	1,598.7	429.2	1,532.9	513.1
Sim. financing/Loans	0.068	0.166	0.076	0.196	0.065	0.159

The statistics are calculated for a universe of 122 banks (26 program, 96 non-program) between 1998 and 2000. Loanable funds: the sum of equity, deposits and other liabilities minus the reserve requirements for each type of liability (for example 20% for checking accounts and 5% for 90 day deposits, 0% for one year deposits and so on). Program banks hold on average 10.2% of total assets, 11.2% of total loans and 12.1% of total deposits of the banking system.

Table 5: Program Firm Loans' Descriptive Statistics

Variable	Mean	Std. Dev.	Min	Max	Median
Amount of loan ($)	9,438.4	4,322.2	500	26,666	10,000
Value of collateral posted	10,527.5	9,751.9	0	350,000	10,000
Interest rate (%)	13.74	1.302	11.5	16	13.5
Grace period (months)	2.15	4.32	0	47	0
Frequency of payments (months)	1.30	1.10	1	6	1
Number of payments	33.19	13.38	0	48	36
Duration (months)	35.60	11.72	1	48	36

* Source: Program database, Secretaría de la Pequeña y Mediana Industria, Ministry of Economy, Government of Argentina. The table is based on 12,192 observations where each observation corresponds to a program loan. Duration is the number of months that results when multiplying the frequency of payment times the number of payments.

Table 6: Regression of Actual Program Financing on Simulated Available Financing

	Actual Financing (growth)		Participation Dummy	
	(1)	(2)	(3)	(4)
Simulated Financing (growth)	0.516***	0.678***	0.832***	0.169***
	[0.133]	[0.115]	[.235]	[0.058]
Bank FE	Yes	No	Yes	Yes
Time dummies	Yes	No	Yes	Yes
Observations	1203	1203	1659	7995
R-squared	0.22	0.04	0.15	0.21
Sample	Program	Program	Program	All

Robust standard errors in brackets clustered at the bank level. * significant at 10%; ** significant at 5%, *** significant at 1%. Each observation corresponds to a bank-month cell. Specifications 1 and 2 exclude observations where actual financing is zero at month t-1. Thus the sample is restricted only to bank-months where banks held some program financing. The participation dummy is equal to one if the program financing of bank i increased at month t.

Table 7: Regression of Actual and Simulated Financing Expansion Growth on Past Deposit Growth (Bank and Month FE)

	Actual Financing (growth)	Simulated Financing (growth) Program banks	Simulated Financing (growth) All banks
	(1)	(2)	(3)
$DepositGrowth_{t-1}$	-0.028	0.02	0.002
	[0.049]	[0.018]	[0.002]
$DepositGrowth_{t-2}$	-0.162***	-0.015	-0.001
	[0.058]	[0.011]	[0.003]
$DepositGrowth_{t-3}$	-0.094	-0.021	0
	[0.086]	[0.016]	[0.004]
$DepositGrowth_{t-4}$	-0.111*	-0.027	-0.002
	[0.055]	[0.019]	[0.003]
Observations	1001	1003	5818
R-squared	0.31	0.85	0.88

* significant at 10%; ** significant at 5%; *** significant at 1%. Robust standard errors in brackets, clustered at the bank level. All specifications include a full set of bank and month dummies.

Table 8: First Stage: Regression of Liquidity on Simulated Credit Expansion Growth (Bank and Month FE)

Liquidity	Program banks (1)	All banks (2)	Non-program banks (3)
Simulated Financing Expansion Growth	0.077***	0.033**	0.013
	[0.022]	[0.012]	[0.015]
Observations	1310	5377	4067
R-squared	0.19	0.08	0.08

* significant at 10%; ** significant at 5%; *** significant at 1%. Robust standard errors in brackets, clustered at the bank level. All specifications include a full set of bank and month dummies. Liquidity is defined as the loanable fund growth, where loanable funds are equity plus deposits plus other liabilities minus reserve requirements.

Table 9: OLS and 2SLS Estimates of the Lending Liquidity Sensitivity (Bank and Month FE)

	OLS	2SLS	2SLS
Sample	All waves	All waves	Final waves
Loan growth	(1)	(2)	(3)
1. Instrument: Sim. Finanacing Expansion			
Liquidity	0.307***	0.481***	0.745***
	[0.074]	[0.170]	[0.139]
# Banks	117	117	113
Observations	6,671	6,436	4,654
R-squared	0.15	0.14	0.12
2. Instrument: Deposit Growth			
Liquidity			0.361***
			[0.099]
# Banks			113
Observations			4,654
R-squared			0.17

* significant at 10%; ** significant at 5%; *** significant at 1%. Robust standard errors in brackets, clustered at the bank level. All specifications include a full set of bank and month dummies. Liquidity is defined as the loanable fund growth, where loanable funds are equity plus deposits plus other liabilities minus reserve requirements.

Table 10: 2SLS Estimates of the Lending Liquidity Sensitivity for banks of Different Size and Capitalization (Bank and Month FE)

Loan growth	(1)	(2)	(3)
Liquidity	0.745***	0.692***	0.627***
	[0.139]	[0.145]	[0.147]
Liquidity x Small		0.012	
		[0.221]	
Liquidity x LowCap			0.063
			[0.190]
# Banks	113	113	113
Observations	4,654	4,654	4,654
R-squared	0.12	0.12	0.12

* significant at 10%; ** significant at 5%; *** significant at 1%. Robust standard errors in brackets, clustered at the bank level. All specifications include a full set of bank and month dummies. Liquidity is defined as the loanable fund growth, where loanable funds are equity plus deposits plus other liabilities minus reserve requirements. The sample is restricted to include only the final waves of the program. Of the program banks in the reduced sample, 40.7% are classified as small and 25.9% as low capitalized. Of the non-program banks, 51.0% are classified as small and 14.9% as low capitalized..

Table 11: Loan and Loan Recipient Sample Summary Statistics, by Borrower Type

	All	New Borrowers	Old Borrowers
Number	750,526	130,201	620,325
Loan Characteristics			
Loan amount ($)	16,691	11,776	17,722
	[226,660]	[260,858]	[218,790]
Collateral/Loan	0.123	0.118	0.124
	[0.301]	[0.312]	[0.299]
Loan Performance			
Default after 12 months (yes=1)	0.122	0.191	0.104
	[0.328]	[0.393]	[0.306]
Default after 24 months (yes=1)	0.168	0.228	0.153
	[0.374]	[0.420]	[0.359]
Borrower History			
Total bank debt			58,551
			[601,468]
Past non-performing loan (yes=1)			0.141
			[0.348]

Means and standard deviations (in brackets) are reported. Statistics are estimated from the post-1998 sub-sample. Each observation corresponds to a new loan issued during the sample period. Default after 12 (24) months is a dummy equal to one if the loan is non performing 12 (24) months after the loan is issued. Past non-performing loan is a dummy equal to one in the loan recipient has any non-performing debt during the 12 months previous to the loan issuance. A loan recipient is classified as *new* if it has no previous credit with the issuing bank, and *old* otherwise.

Table 12: Bank Liquidity and Loan Risk – IV Estimates of Loan Default Rate on Liquidity Expansion Dummy (Bank, Month and Industry Fixed Effects)

	Loan with problems after:	
	12 months	24 months
	(1)	(2)
1. All Loans		
Liquidity expansion bank-month	-0.004	-0.009
	[0.028]	[0.020]
Observations	750,563	750,563
R-squared	0.04	0.05
2. New Borrowers		
Liquidity expansion bank-month	0.038**	0.017
	[0.018]	[0.016]
Observations	130,201	130,201
R-squared	0.02	0.04
3. Old Borrowers		
Liquidity expansion bank-month	-0.002	-0.012
	[0.022]	[0.018]
Observations	620,325	620,325
R-squared	0.04	0.05
4. New Borrowers w/history		
Liquidity expansion bank-month	0.176**	0.161**
	[0.062]	[0.067]
Observations	5,488	5,488
R-squared	0.07	0.09

Robust standard errors in brackets, clustered at the bank level. All specifications include bank and month fixed effects. * significant at 10%; ** significant at 5%; *** significant at 1%. Each observation corresponds to a loan made by bank i to firm j at month t. The dependent variable in columns 1 and 2 (3 and 4) is a dummy equal to one if the loan repayment is at least six months late, the loan is defaulted or the loan recipient has filed for bankruptcy 12 (24) months after issued. All specifications include bank, industry and month dummies. The liquidity expansion dummy is instrumented with the predicted probability of participation of bank i in a wave that begins at month t.

Table 13: Bank Liquidity, Collateral and Borrower Past Performance: IV Estimates of Loan Collateral to Debt Ratio and Default History on Liquidity Expansion Dummy (Bank, Month and Industry Fixed Effects)

	Collateral/Loan (1)	Bad Past Performance (2)
1. All Loans		
Liquidity expansion bank-month	-0.010**	
	[0.004]	
Observations	750,526	
R-squared	0.09	
2. New Borrowers		
Liquidity expansion bank-month	-0.034*	
	[0.019]	
Observations	130,201	
R-squared	0.05	
3. Old Borrowers		
Liquidity expansion bank-month	0.002	0.047*
	[0.008]	[0.025]
Observations	620,325	620,325
R-squared	0.14	0.07
4. New Borrowers w/history		
Liquidity expansion bank-month	-0.068*	0.039***
	[0.037]	[0.013]
Observations	5,488	5,488
R-squared	0.20	0.02

Robust standard errors in brackets, clustered at the bank level. All specifications include bank, industry and month dummies. * significant at 10%; ** significant at 5%; *** significant at 1%. Each observation corresponds to a loan made by bank i to firm j at month t. The dependent variable in columns 1 and 2 is the proportion of the value of the loan covered with collateral. The dependent variable in column 3 is a dummy equal to one if the loan recipient has some non-performing debt outstanding (non-performing is defined as at least six months late in repayment). The liquidity expansion dummy is instrumented with the predicted probability of participation of bank i in a wave that begins at month t. The small loans dummy is equal to one if the amount of the loan is in the lowest quintile of the loan amount distribution.

Table 14: Collateral and Past Performance as Predictors of Default: Probit Estimation of the Probability of Default as a Function of the Collateral to Debt Ratio and Past Defaults (Bank, Month and Industry Fixed Dummies)

	Probability of Default	
	OLS	Probit (a)
	(1)	(2)
1. All Loans		
Collateral/Debt	-0.052***	-0.052***
	[0.004]	[0.004]
Observations	750,526	750,526
R-squared (pseudo)	0.04	0.04
2. New Borrowers		
Collateral/Debt	-0.104***	-0.109***
	[0.005]	[0.005]
Observations	130,238	129,804
R-squared (pseudo)	0.08	0.08
3. Old Borrowers		
Collateral/Debt	-0.035***	-0.038***
	[0.004]	[0.005]
Past Default Dummy	0.544***	0.554***
	[0.002]	[0.003]
Observations	620,325	617,863
R-squared (pseudo)	0.21	0.17
4. New Borrowers w/history		
Collateral/Debt	-0.096***	-0.104***
	[0.019]	[0.022]
Past Default Dummy	0.339***	0.367***
	[0.065]	[0.069]
Observations	5,488	5,488
R-squared (pseudo)	0.08	0.07

Robust standard errors in brackets, clustered at the firm level (222,146 clusters in the entire sample). All specifications include bank, industry and month dummies. * significant at 10%; ** significant at 5%; *** significant at 1%. Each observation corresponds to a loan made by bank i to firm j at month t. The small loans dummy is equal to one if the amount of the loan is in the lowest quintile of the loan amount distribution.
(a) Marginal effects evaluated at the sample mean are reported.

7. Figures

Figure 1: Time Series Evolution of Loans and Deposits in the Banking System, monthly data from 1992 to 2001

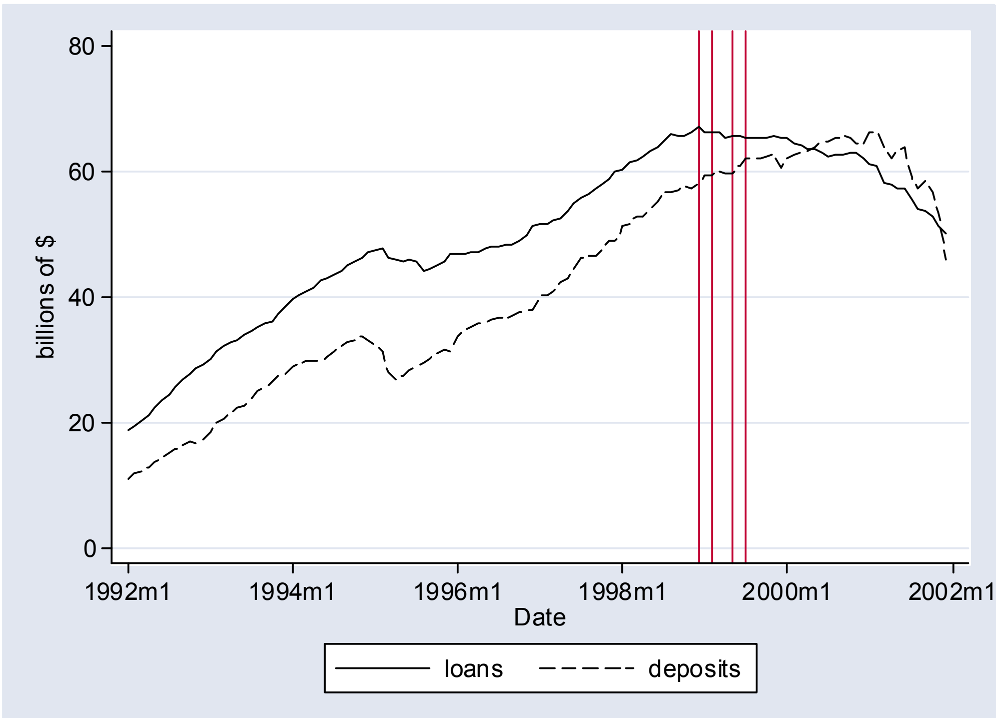


Figure 2: Flow of Program Financing and Number of Participating Banks, by Year

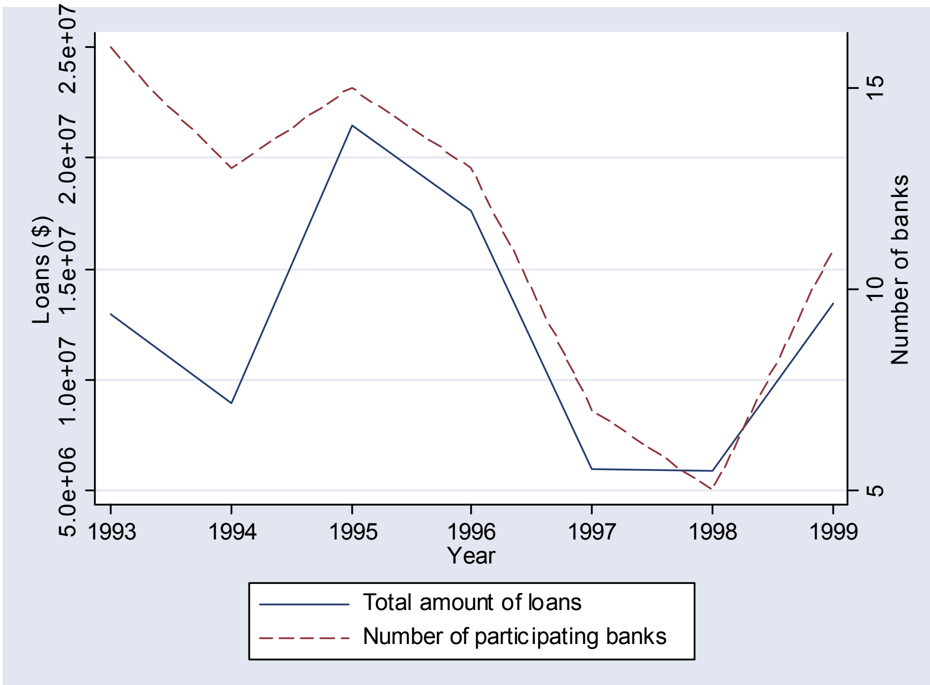


Figure 3: No Financing Frictions: Profit Maximizing Choice of Loans when Subsidized Financing Increases

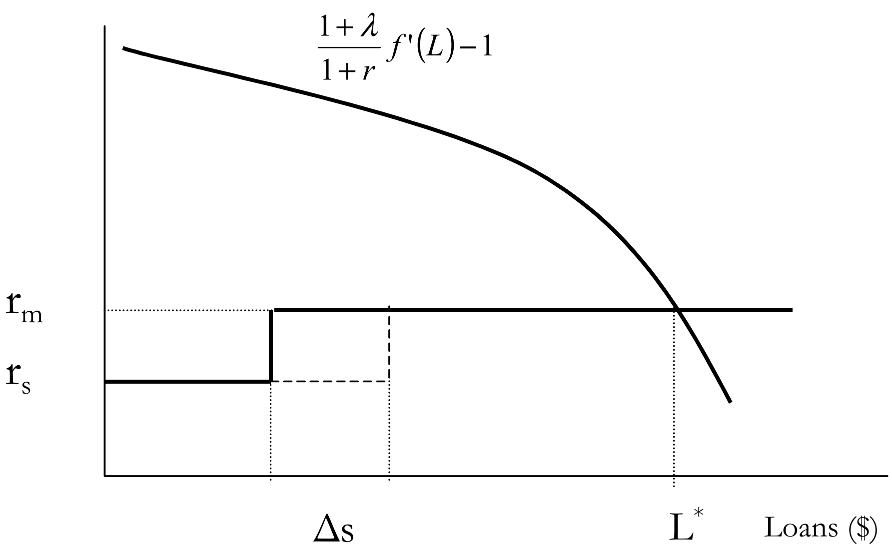


Figure 4: Financing Frictions: Profit Maximizing Choice of Loans when Subsidized Financing Increases

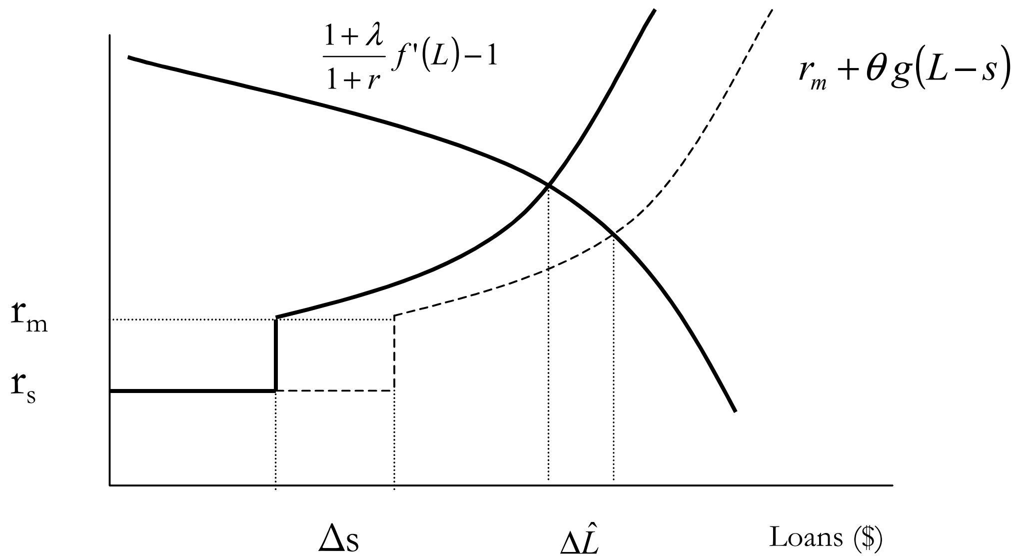
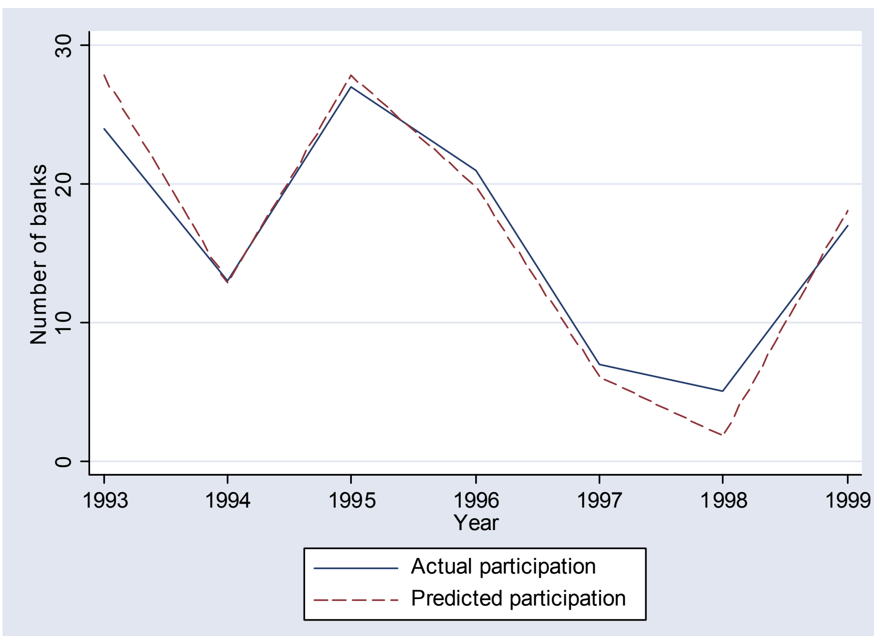


Figure 5: Actual and Predicted Number of Bank Participations in a Wave, by Year



*Participations in a wave are higher that participating banks per year (last graph) when there is more than one wave in a year

Figure 6: Participating vs. Non-Participating Bank Difference in the log Average Loanable Funds, and log of Stock Program Financing (normalized)

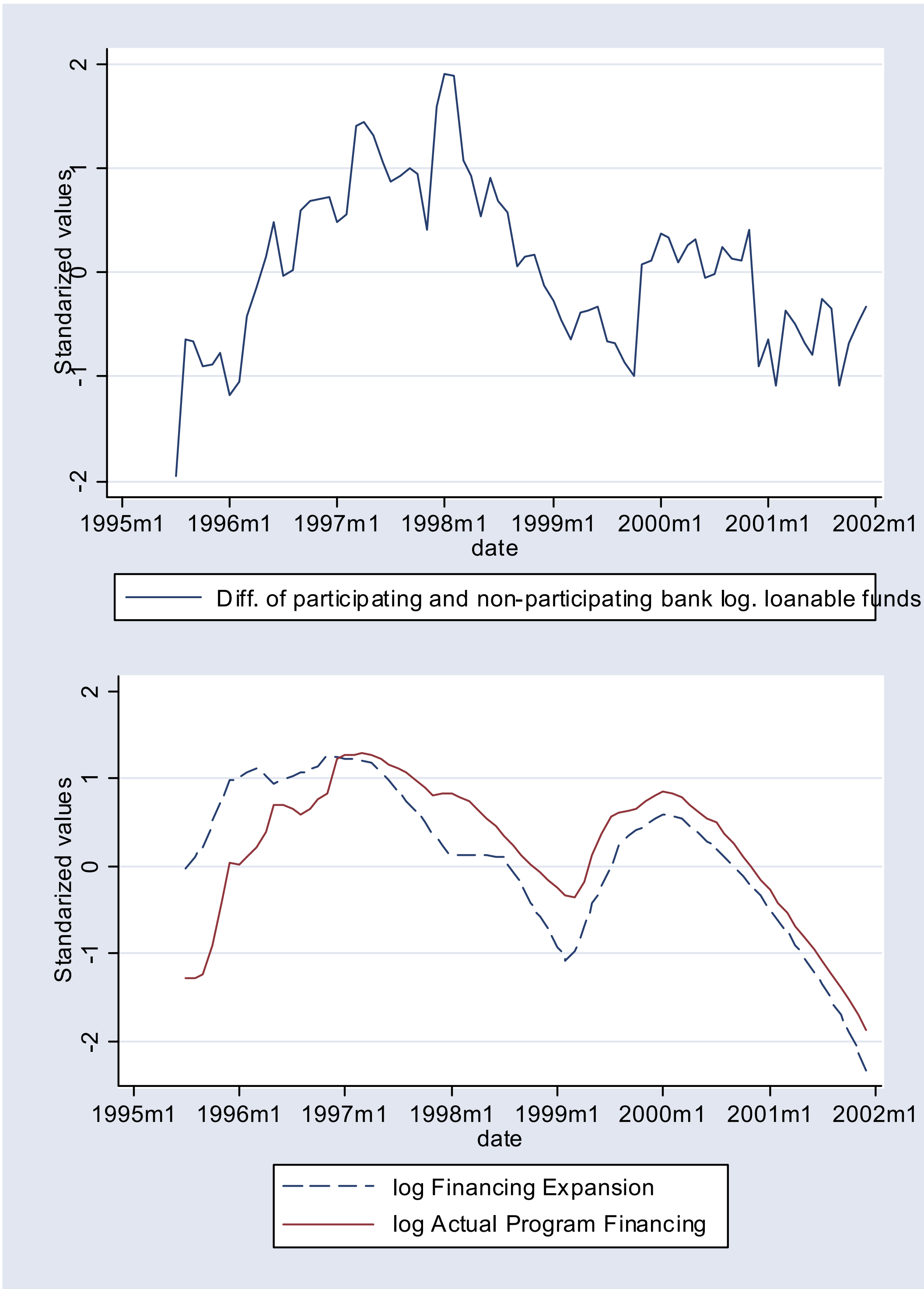


Figure 7: Log of Average Loanable Funds of Participating and Non-Participating Banks (normalized)

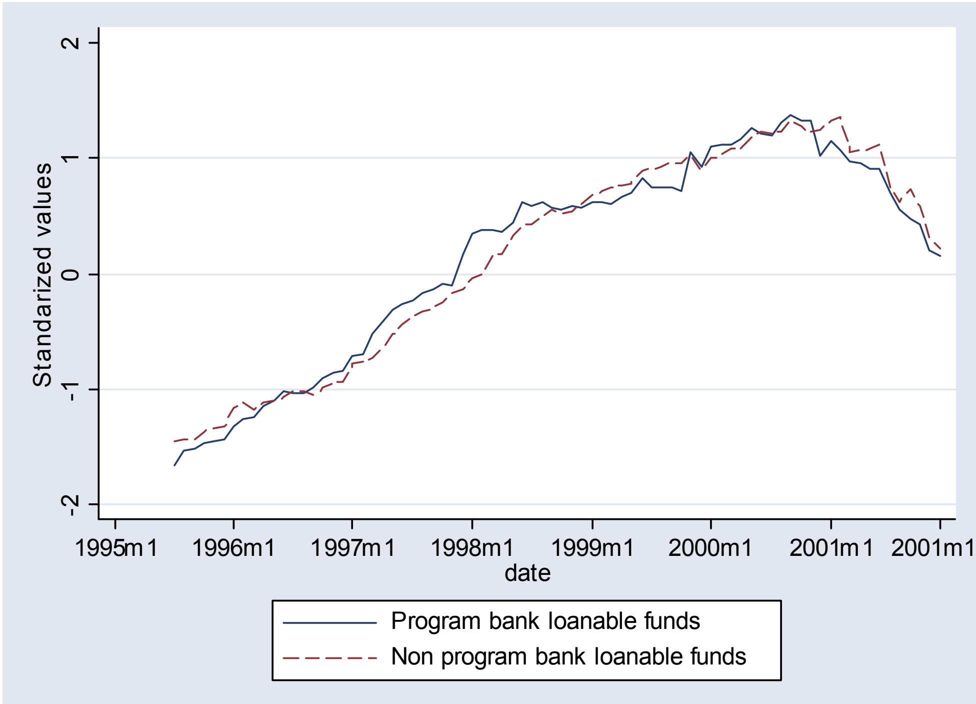


Figure 8: Difference in the log Average Loanable Funds and Loans of Participating vs. Non-Participating Banks

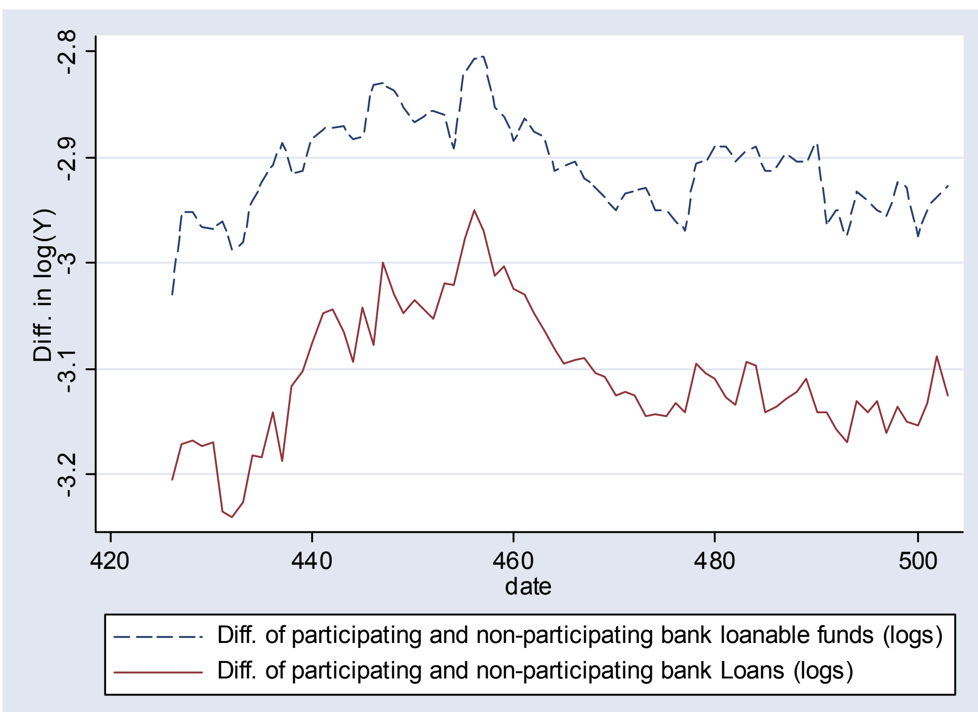


Figure 9: Collateral to Loan Ratio of the Flow of Loans in the Sample Period

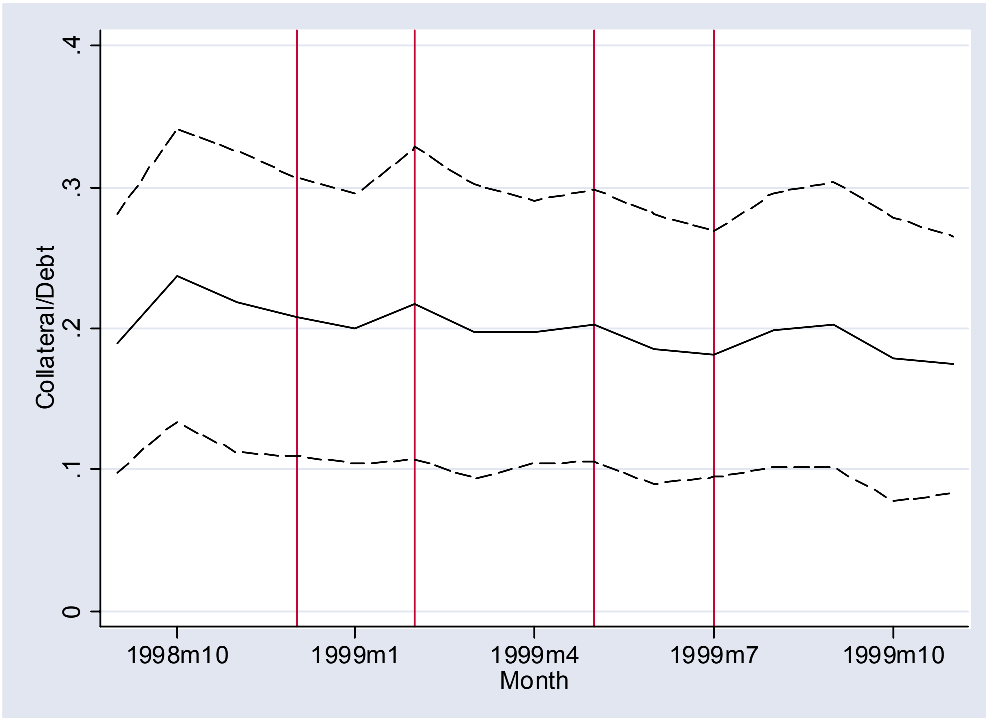


Figure 10: Lagged Fraction of Debt in Good Standing of Loan recipients in the Sample Period

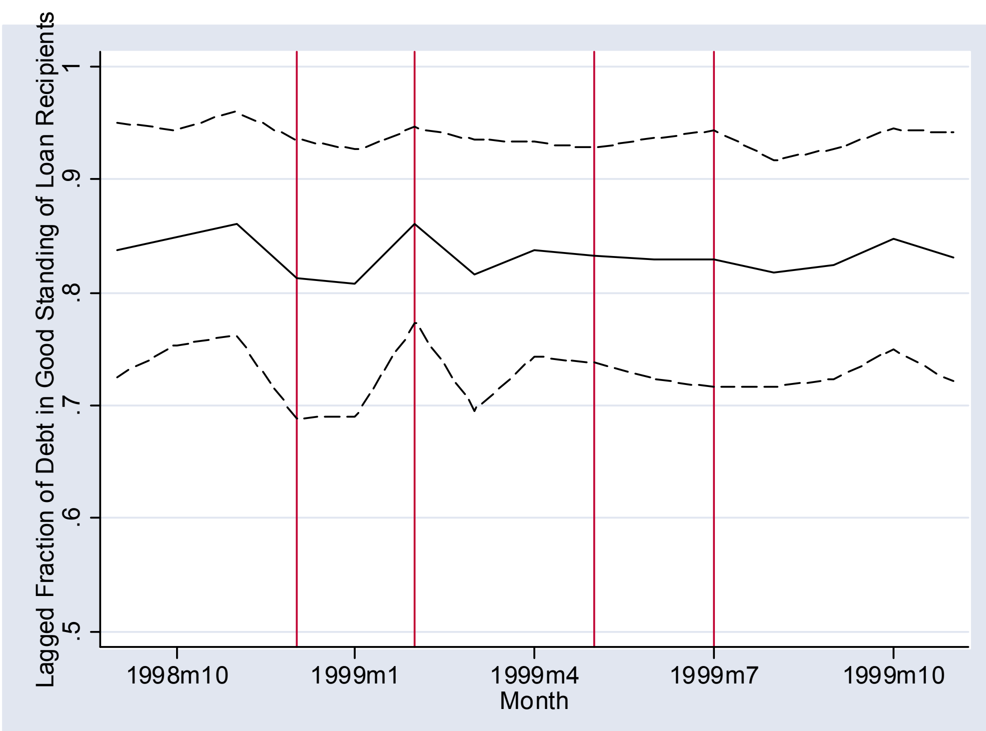


Figure 11: Time series of Total Loans and Deposits in the Banking System in the Sample Period