Constrained Banks, Constrained Borrowers:
Bank Liquidity Constraints and Firm Access to External Finance

DANIEL PARAVISINI* 

September 2005

Abstract. This paper provides evidence that small banks are liquidity constrained, and that positive liquidity shocks improve the financial position of their borrowers. To test for liquidity constraints, I show that bank lending is sensitive to exogenous cash windfalls received from the Argentine government. Lending increases by $0.66 for each dollar of additional liquidity, and that the marginal loans are not more likely to default than the inframarginal ones. Using new loan level data from a public credit bureau, I track the effects of the liquidity shock on the financial position of bank borrowers. When banks receive a cash windfall, their borrowers experience a 7.7% increase in total bank financing and a 0.6 percentage point decrease in the probability of bankruptcy. I finally show some evidence that adverse selection prevents full arbitrage of lending opportunities by competing, potentially unconstrained banks. (JEL: G21, E50, D82)

* Columbia University GSB. I thank Abhijit Banerjee, Esther Duflo, Sendhil Mullainathan and Antoinette Schoar for invaluable comments and discussions. This work also benefited greatly from the thoughts of all the participants of the finance seminars at Columbia GSB, Kellogg (Northwestern), Universitat Pompeu Fabra, Smith (Maryland), Sloan (MIT), Stanford GSB, Stern (NYU), Stockholm School of Economics, Stockholm University, UT Austin, Yale SOM; the banking seminars at the New York Federal Reserve Bank and the Board of Governors of the Federal Reserve Bank; and the development economics seminar at MIT. I am grateful for comments from Adam Ashcraft, Darrell Duffie, Iván Fernández-Val, Andrew Hertzberg, Arvind Krishnamurthy, Owen Lamont, Alexis León, Jun Pan, Francisco Pérez-González, Tano Santos, Sheridan Titman and Jeffrey Zwiebel.
The question of how bank liquidity constraints affect lending behavior, economic activity and business cycles has long been of concern to the literature on financial institutions. Financially constrained banks are the proposed culprit behind recent accounts of the Great Depression and the ‘capital crunch’ of the early 90's in the U.S. (Bernanke 1983; Sharpe 1995). Liquidity constraints are also key for the existence of a lending channel of transmission of monetary policy (Bernanke and Blinder 1988; Holmstrom and Tirole 1997; Stein 1998). More recently, liquidity risk and the fragility of bank capital structure have been linked to banks’ ability to create liquidity and force borrower repayment (Diamond and Rajan 2000; 2001; Kashyap, Rajan and Stein 2002). However, assessing the effect of bank liquidity on lending behavior and borrower outcomes poses a difficult empirical challenge. Sorting out the effect of bank liquidity from other shocks to the demand and supply of credit is one of the two main motivations of the empirical work on the lending channel during the last decade (Peek and Rosengren 1997; Kashyap and Stein 2000; Calomiris and Mason 2003; Khwaja and Mian 2005). The second motivation has been to evaluate whether shocks to bank liquidity have any real effect on corporate finance and firm outcomes (Kashyap, Stein and Wilcox 1993; Kashyap, Lamont and Stein 1994; Peek and Rosengren 2000; Hubbard, Kuttner and Palia 2002).

This paper addresses both issues: it performs a consistent test for bank liquidity constraints, and provides evidence that shocks to the financial position of a bank affects the access to credit and probability of survival of its borrowers. To identify the effect of liquidity I use cash windfalls from a government program as an exogenous source of variation in the financial position of small banks in Argentina. I exploit the fact that the size, timing and cross sectional distribution of the cash windfalls were governed by a predetermined bureaucratic formula, unrelated to bank marginal cost of capital or investment opportunities. Then, using novel data from a Public Credit Registry to construct the credit history of every bank borrower, I follow the effect of the liquidity shock on loan portfolio performance and firm access to credit and probability of bankruptcy. The panel structure of the loan level data allows measuring the ex-post performance of loans issued during the cash windfalls. This provides the relevant information on marginal investment and outcomes associated with a liquidity shock.
The results indicate that banks expand lending by $0.66 for every dollar of additional liquidity. This finding is not consistent with the Modigliani-Miller proposition for banks and suggests that banks were liquidity constrained before receiving the cash windfalls. I show that this sensitivity is larger for smaller and less capitalized banks, although the cross sectional variation is small relative to the absolute magnitude of the lending response to liquidity. I then show that when the endogeneity of the liquidity shock is not accounted for, the magnitude of the lending response is underestimated by a factor of 2. The results suggest, contrary to the prevailing view, that identification problems can introduce a bias against finding evidence of a lending channel.

A positive sensitivity of lending to liquidity is also consistent with free cash flows theories of investment (Jensen 1986). To rule out this interpretation I use the fact that the free cash flow and the liquidity constraints hypotheses have contrasting predictions on the risk of the marginal loan. Under the free cash flow view, an exogenous expansion in available financing leads unambiguously to a deterioration of the quality of bank investment. The ex-post performance of marginal loans suggest this is not the case: I find that loans financed during liquidity expansions are not more likely to default than loans issued in other periods. This finding is consistent with the liquidity constraints interpretation and, under plausible assumptions, suggests that constraints prevent banks from undertaking profitable lending opportunities.

The paper then investigates the effect of the liquidity shock on bank borrowers. Even if small banks in the financial system are liquidity constrained, investment and other firm outcomes will not be affected when firms can obtain finance from other bank or non-bank sources. On the contrary, I find that receiving a loan from a bank that experienced a cash windfall increases the total bank finance available to a firm by 7.7% and reduces its probability of default by 0.6 percentage points. Furthermore, the decline of the default rate is larger for firms in industries that are more dependent on external finance (as in Rajan and Zingales 1998). The findings suggest that firms are also financially constrained, and that these constraints are relaxed when lenders receive positive liquidity shocks.

The final section of the paper provides evidence that suggests adverse selection plays an important role in preventing borrowers from substituting between sources of bank financing.
Banks allocate less than 0.5% of their loan portfolio to borrowers that have never obtained finance from them but are switching from another lender. And when banks do lend to these switching borrowers, the loans tend to perform worse than predicted according to observable borrower characteristics. The opposite pattern appears when banks lend to borrowers with a pre-existing relationship: 87% of the flow of funds is allocated to these borrowers, and the loans perform better than expected given loan recipient characteristics. These findings are consistent with the predictions of well known models of private information in lending relationships (Sharpe 1990; Rajan 1992; Petersen and Rajan 1995; Von Thadden 2004).

Overall, the findings of this paper corroborate the lending channel hypothesis applied to small banks. More importantly, the results indicate that a shock to the liquidity of small banks affect firm outcomes and access to credit, even in a banking system characterized by a significant presence of large, multi-national financial intermediaries and a regulatory system that encourages entry and competition (Calomiris and Powell 2000). There is a low elasticity of substitution across sources of financing for borrowers of small banks even when there are other unconstrained providers of finance in the banking system. Small banks will play an instrumental role in propagating and amplifying the real effects liquidity shocks to the banking system.

The paper proceeds as follows. Section I provides the institutional background on the Argentine banking sector in 1998 and 1999, discusses the analytical framework for testing bank liquidity constraints, and describes the source of the liquidity shock. Section II describes in detail the empirical strategy of the paper, emphasizing how the government program rules are exploited to create an exogenous instrument for bank liquidity. Section III describes the data sources and variable definitions. Section IV presents the results on the effect of the liquidity shock on bank and firm outcomes. Section V provides evidence on adverse selection and Section VI concludes.

I. Setting and Conceptual Background

A. The Argentine Banking System

The Argentine banking system in 1999 was characterized by significant participation of foreign owned banks, which held 48% of the assets of the financial system. The average bank
in the Argentine system had $1.1 billion in assets, slightly below the assets of the average bank in the U.S. in 1996, when assets are consolidated over all banks that belong to the same holding company ($1.2 billion, see Ashcraft (2003, forthcoming)). Most government owned banks were privatized between 1994 and 1996, but by 1999 government owned banks still held 27% of the assets of the banking system. The rest of the banking system at the time consisted of smaller, locally owned banks. The average local bank has about one fourth of the assets of the average foreign bank, and one sixth of the assets of the average government bank.

This paper measures the extent of financing frictions among small locally owned banks in this context. Measuring the extent of financing constraints in this particular group of banks is relevant because frictions are more likely to be prevalent among them. Large foreign banks have larger internal capital markets from which to draw funding (Stein 1997; Berger et al. 2003), and government agencies tend to be characterized by ‘soft’ budget constraints (Kornai 1979; 1986). More importantly, focusing on small banks allows addressing the question of whether liquidity shocks matter for firm level outcomes when there are other potentially unconstrained lenders available to fill the gap. The ability of foreign banks to supply credit to sectors traditionally covered by local banks has been questioned by recent empirical work (Mian 2004), and is one of the central points in the debate around the impact of the globalization of the banking industry on the availability of finance in emerging markets.

The institutional and macroeconomic environment in Argentina during the period of interest is particularly suitable for studying bank liquidity issues. The regulatory setting in which Argentine banks operate has very similar features than the regulatory setting in more developed financial markets (Mishkin 2000; 2001). Furthermore, the Argentine regulatory system was one of the first to adopt the recommendations of Basel II (Calomiris and Powell 2000), and understanding bank behavior within this institutional setting becomes even more important as the new rules become standard in emerging markets. Finally, the macroeconomic conditions during the period of study stacks the cards against finding evidence of banks being liquidity constrained since the banking system was operating amidst increasing liquidity and stalling investment opportunities. Real GDP grew at an annual average of 0.1% between 1998
and 2000, while total bank deposits experienced an average yearly growth of 9.1% during the same period.

B. Testing for Financing Constraints of Banks

There is a large empirical literature on the lending channel and credit crunches tests for financing constraints at the bank level. This body of empirical work is based on the following prediction of the Modigliani-Miller theorem applied to banks: changes in the financial position of an unconstrained bank will not affect its lending behavior. Ceteris paribus, observing that lending is correlated with changes in bank liquidity is interpreted as evidence that banks face financing frictions. The argument holds even when the source of the shock to the financial position is a change in insured deposits, which are priced below the market rate. The marginal cost of capital of a bank will be given by the cost of market priced sources of financing (e.g. subordinated debt, equity), and this marginal cost will not be affected by the infra-marginal change in deposits in a Modigliani-Miller world (Stein 1998).

The usual empirical specification looks at the relationship between loan growth and a variable that affects bank liquidity, such as changes in monetary policy (Bernanke and Gertler 1995; Hubbard 1995), deposit growth (Jayaratne and Morgan 2000), internal cash (Ostergaard 2001) or stock price (Peek and Rosengren 1997). This standard specification can be written as:

\[ \ln L_{it} - \ln L_{it-1} = \alpha_i + \alpha_t + \beta_0 D_{it} + \gamma x_{it} + \epsilon_{it} \]  

(I-1)

where \( L_{it} \) are total loans of bank \( i \) at month \( t \) (the changes in logs transformation gives the proportional rate of growth), \( D_{it} \) represents a measure of the liquidity shifter, \( \alpha_i \) and \( \alpha_t \) are bank and month fixed effects, \( x_{it} \) is a set of controls and \( \epsilon_{it} \) is a stochastic error term. Under the null hypothesis of no financial frictions, \( \beta_0 = 0 \).

The main concern with the standard specification is that the sources of variation in bank liquidity are potentially correlated with other factors affecting either the supply or the demand of credit. For example, an increase in deposits might decrease the risk profile of the bank, lowering the marginal cost of capital and inducing additional lending. Alternatively, the same increase in deposits may be a signal better future lending prospects (higher marginal returns on lending). In both cases, changes in deposits will be correlated with lending even when banks are unconstrained. In other words, an estimate of \( \beta_0 > 0 \) in (I-1) could be obtained in the absence of financing constraints.
The difficulty of tackling this identification issue is attested by the amount of work devoted to address it in the literature. One approach has been to control explicitly for bank investment opportunities by introducing Tobin’s $q$, or GDP growth among the set of controls $x$. A second, to look at the differences in the lending-liquidity sensitivity across banks that are more likely to face financing constraints according to observable characteristics, such as size, capital, holdings of liquid assets and affiliation with multi-bank holdings (Kashyap and Stein 2000; Kishan and Opiela 2000; Ashcraft 2003, forthcoming). And third, by looking at changes in the composition of bank finance within firms when banks receive liquidity shocks (Kashyap et al. 1993; Kashyap et al. 1994; Khwaja and Mian 2005).

Each of these approaches has potential drawbacks. The observed correlation between investment and cash flow can be entirely driven by measurement errors in $q$, and bank specific changes in investment opportunities in the first approach (as noted for non-financial firms by Poterba 1988; Erickson and Whited 2000; Gomes 2001). Also, the cross sectional patterns that appear in the second approach are consistent with models without financing frictions (Alti 2003; Moyen 2004), and are shown to appear in the data even among unconstrained non-financial firms (Kaplan and Zingales 1997; 2000). And the papers using the third approach look at large shocks to deposits which affect both bank liquidity and risk profile (cost of capital), and is difficult to disentangle which of the two effects is driving the changes in lending behavior.

Ideally, to test for financial constraints one requires a source of variation in the financial position of a bank that can be decoupled from variations in the marginal cost of capital, investment opportunities or other factors affecting the demand or supply for bank credit. This ‘natural experiment’ approach is adopted in more recent investment-cash flow literature (Blanchard, Lopez-de-Silanes and Shleifer 1994; Lamont 1997; Rauh 2004), and also used in this paper. I will exploit the fact that small banks in Argentina received cash windfalls from the government in several installments during 1999. These cash windfalls provide an exogenous source of variation in bank liquidity that allows testing for the financing constraints hypothesis. I will use a variation to the standard specification (I-1) with the change in total loanable funds of bank $i$ at month $t$, $F_{it}$, as the dependent variable:

$$\ln L_{it} - \ln L_{it-1} = \alpha_i + \alpha_t + \beta_0 (\ln F_{it} - \ln F_{it-1}) + \epsilon_{it}$$ (I-2)
The parameter of interest, $\beta_0$, will be estimated using expected cash windfalls, $EC_t$, as an instrument for bank loanable funds using 2SLS. The instrument—expected cash windfalls—is constructed exploiting institutional features of the government program that originated the cash windfalls. As will be discussed in detail in Section II, these features were unrelated to the financial conditions of the recipient banks or the credit market during 1999. Thus, the 2SLS estimate of $\beta_0$ represents the sensitivity of bank lending to changes in bank liquidity. An estimate of $\beta_0 > 0$ will be consistent with financially constrained banks.

C. Source of the Liquidity Shock: MYPES program

The Credit Program to Small and Medium Sized Firms (MYPES for its acronym in Spanish) 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 institution’s lending to small businesses. The MYPES falls into the category of what is known in the development agency jargon as an on-banking or a two-step lending program (Barger 1998). 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. The MYPES required banks to issue $1$ of loans to eligible borrowers for every $0.75$ of program financing received. Firms with less than 20 workers and less than $200,000$ in annual sales were eligible to receive program loans.

In sharp contrast with the purported intention of the program, I show in previous research (Paravisini 2003) that eligible borrowers’ debt increased by less that 10 cents for every dollar of program financing received by participating banks. Banks circumvented the allocation rule by picking the best performing borrowers among their eligible clients and re-labeling existing debt as ‘program loans’. This is evidenced in Figure 1, which shows monthly evolution of total bank debt of a sample of 2,596 firms that received the program loans. Debt is plotted for the 12 months prior and following the date each firm received the program loan (month 0). Program loan recipient’s debt with the bank that intermediated the program loan did not change at $t=0$, when they received the program loan. Program loans substituted dollar for dollar other preexisting debt of bank clients. The evidence suggests that banks were de facto not
required to increase lending in the margin to the target borrowers or to any other. Thus, I will interpret all the empirical results assuming banks allocated resources to further their own objectives, regardless of the de jure requirements of the program rules.$^4$

Program financing was allocated in 12 waves between 1993 and 1999. The yearly flow of program financing, plotted in panel 1 of Figure 2, displays two peaks: one during years 1995 and 1996 and another one in 1999. The first peak coincides with the aftermath of massive deposit drains triggered by the Tequila crisis. This may raise the concern that the timing and size of the program waves were decided in response to the liquidity needs of the banking system. The second peak, however, was driven by an ‘administrative rush’ in 1999. The IDB made the availability funding for a second phase of the program conditional on the complete execution of the budget allocated to the first phase before year 2000. As a result, all the resources remaining in the program budget were lent to banks in four waves from December 1998 through November 1999 (waves 9 through 12 in panel 2 of Figure 2). I will restrict the sample in the empirical analysis to the final four waves of the program (January 1998 to December 2000). Since the timing and amount of waves in this period were determined by the administrative rush, each wave is likely to provide a separate shock to liquidity that was driven by factors unrelated to aggregate liquidity needs of the banking system.$^5$ I corroborate that this assumption holds in the data in the empirical strategy section that follows.

A month prior to the beginning of each wave, the Central Bank announced publicly the amount to be distributed and banks submitted an application to participate. The wave resources were allocated among all participating banks according to an administrative formula based on bank characteristics. 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. Each participating bank was assigned a point score according to these characteristics and the wave resources were allocated proportionally to each bank’s score.$^6$ Banks had three months to use the allocated resources or pay a penalty equal to twice the interest rate on the unused balance. The repayment schedule of the program financing received by banks was to follow the same repayment schedule banks attached to the program loans to firms.

Finally, 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 or the cost of capital, which allows focusing on the partial equilibrium effects of the liquidity expansion. 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. Nevertheless, participating banks held at all times during the sample period liabilities at the market price (e.g. subordinated debt) which suggests that cash windfalls did not affect the marginal cost of financing of banks, a hypothesis that will be tested in the empirical strategy section next.

II. Empirical Strategy

To identify the effect of bank liquidity on bank outcomes I intend to exploit the variation in bank liquidity induced by the MYPES program. Section I.B. argued that this empirical strategy would be implemented using expected cash windfalls ($E(C_t)$) as an instrument for bank loanable funds ($F_t$). The two identifying assumptions of the instrumental variable approach are that the expected cash windfalls variable is correlated with changes in bank loanable funds, but uncorrelated with changes in the cost of capital, investment opportunities, deposit shocks or other factors that affect bank liquidity or the lending behavior (exclusion restriction).

To best understand why it is necessary to construct the expected cash windfalls variable, it is helpful to discuss how the actual cash windfalls variable does not constitute a valid instrument for bank liquidity. Since bank participation in the program was voluntary, it is likely that banks with tighter cash positions or better investment opportunities applied for program financing. Self selection into the program introduces a correlation between cash windfalls and bank lending behavior that would bias an estimate of the sensitivity of lending to liquidity using 2SLS in specification (I-2).7

I deal with bank selection by looking only at changes in banks’ decision to participate that are induced by changes in wave size. The choice of changes in wave size as a source of variation in participation has a conceptual rationale that is also consistent with the stylized facts of the participation patterns observed in the data. If program participation involved a fixed administrative cost, then larger program waves would imply larger cash windfalls which would in turn induce higher program participation.8 This is pattern is confirmed in the data,
which shows a substantial and positive time series correlation between the number of participating banks and amount of resources in a wave (Figure 2). Furthermore, the allocation rule of the program assigned larger cash windfalls (for a given wave size) to banks with smaller average loan size and more lending in poor areas. A fixed participation cost would induce higher participation rates among banks with smaller loan sizes and larger fractions of lending in poor areas. This pattern is again present in the data. The average participating bank allocated more than twice of its loan portfolio in poor regions than non-participating banks —15.4% versus 6.3%—, and has an average loan size that is just 25% the average loan size of non-participating banks —$76,000 versus $318,000.9

A. A Model of Program Participation

The stylized facts on participation and wave size can be formalized in a simple model of bank participation with fixed costs and private information. Suppose $N$ banks are deciding at time $t=0$ whether or not to participate in program wave $w$ of size $A_w$. For now assume all banks are equal except for their cost of participation, $\eta$, which is private information and that if $n$ banks participate, each will receive an equal share of the resources in the wave at time $t=1$. The only cost of the program is the participation cost, such that if bank $i$ participates in a wave with $n-1$ other banks, it will make profits of $A_w/n-\eta_{iw}$. Profits at time 1 are a function of the number of banks that participate, which is unknown at time 0 when the participation decision is made. All banks know at time zero is the common knowledge p.d.f. from where the participation costs are drawn, $f(\eta)$. All banks are risk neutral, such that a bank will participate in a program wave when expected profits are positive.

This setup is equivalent to a private value auction and the solution can be described by a cutoff rule: bank $i$ participates if $\eta_{iw} < \eta_{w}^*$. That is, banks will participate in the program if their participation cost at time zero is below a threshold value $\eta_{w}^*$, and will not participate otherwise. The probability any bank $i$ participates in the program is given by:

$$p_i = \int_{0}^{\eta_{w}^*} f(\eta) d\eta$$

and expected profits of bank $i$ in wave $w$ are:

$$E(\pi_i) = A_w \sum_{j=1}^{N-1} \frac{1}{1+j} p_i^{j+1}(1-p_i)^{N-(j+1)} \binom{N-1}{j} \eta_{iw}$$
The sum term represents the expected fraction of the resources in a wave that each bank receives. The interpretation of the first two terms in the sum term is straightforward: bank \( i \) receives a share \( 1/(1+j) \) of the resources in a wave when \( j \) other banks participate, which happens with probability \( p_w^{j+i}(1-p_w)^{N-j-i} \). The last term of the sum represents the number of potential combinations of \( j \) banks that may participate out of \( N-1 \) potential candidates.

Finally, the cutoff \( \eta \) is determined by the value of \( \eta \) that makes the expected profit of participation in (II-2) equal to zero. This participation threshold is the same for all banks given the symmetry assumptions made so far. Substituting \( \eta \) into (II-1) gives an implicit expression for the probability of participation:

\[
p_w = \Pr \left[ \eta < A_w \left( \sum_{j=0}^{N-1+j} \frac{1}{j+N-1} p_w^{j+i}(1-p_w)^{N-j-i} \binom{N-1}{j} \right) \right] \\
(II-3)
\]

The probability of participation \( p_w \) is an increasing function of wave size \( A_w \), which is consistent with the positive correlation between wave size and number of participating banks observed in the data.

The model can be modified to allow the probability of participation to vary across banks. I assume that the resources in a wave are distributed according to the actual formula used to allocate program resources (described in section I.C):

\[
C_{iw} = A_w \left[ \frac{Z_{\text{region}}_{iw}}{2 \cdot \sum_j Z_{\text{region}}_{jw}} + \frac{Z_{\text{size}}_{iw}}{2 \cdot \sum_j Z_{\text{size}}_{jw}} \right] \\
(II-4)
\]

where \( C_{iw} \) is the amount of financing bank \( i \) receives in wave \( w \), \( A_w \) is the amount of resources in wave \( w \), \( n_w \) is the number of banks participating in wave \( w \), and \( Z_{\text{region}} \) and \( Z_{\text{size}} \) are two point scores assigned to each bank according to size and regional distribution of the loan portfolios. Each bank receives a fraction of the resources available in the wave that is proportional to the ratio of their score points relative to the sum of the scores of all participating banks.

Each bank will now have a different participation threshold, \( \eta_{iw}^* \), and a different probability of participation, \( p_{iw} \). The expression for the expected profits of bank \( i \) of participating in wave \( w \) can be summarized as:

\[
E(\pi_{iw}) = A_w G(Z_{\text{region}}_{iw}, Z_{\text{size}}_{iw}, Z_{\text{region}}_{iw}, Z_{\text{size}}_{iw}) - \eta_{iw} \\
(II-5)
\]
The function $G(.)$ is the expression for the expected fraction of resources in a wave assigned to bank $i$. It is the equivalent of the sum term in (II-2) but it is now a function of bank $i$’s region and size scores, and the rest of the potential participant bank’s region and size scores. The key feature of this function is that it is increasing in the point scores of bank $i$. Thus, banks with a higher region and size point scores will be more likely to participate in the program for a given wave size. This prediction of the model is consistent with the stylized facts of the program and is exploited in the empirical strategy of the paper. I use the time series variation in wave size, $A_w$, and the cross sectional variation in the point scores, $Z_{region_i}$ and $Z_{sizei_i}$, as a source of variation of both the decision of a bank to participate in the program and the size of cash windfalls. In other words I use a non-linear interaction between $A_w$, $Z_{region_i}$ and $Z_{sizei_i}$, as an instrument for bank loanable funds in specifications (I-2) and (IV-2).

**B. Identification and Implementation: Expected Cash Windfalls**

The empirical strategy will identify the effect of cash windfalls from the within bank, time series variation in participation due to changes in wave size. The strategy will provide unbiased estimates for the sensitivity of lending to liquidity for the group of banks that switch in and out of the program due to changes in wave size. 2SLS estimation will only take into account the variation in bank liquidity that can be projected on space spanned by the instrument vector, whose only source of time series variation is the change in wave size.\textsuperscript{10} The key identification assumption is that wave size variation is uncorrelated to the time series variation of liquidity needs or investment opportunities of bank B (tested in the next subsection).

The empirical strategy is implemented by predicting the expected cash windfall each bank will receive at each moment in time using solely wave size and the region and loan size scores. I first estimate a probability model of participation based on (II-5). The probability bank $i$ will participate in wave $w$ of the program is given by:

$$p_{iw} = Pr[\eta_w < A_w G(Z_{region_{iw}}, Z_{sizei_{iw}}, Z_{region_{iw}}_w, Z_{sizei_{iw}})_w]$$ (II-6)

An estimate of the probability of participation, $\hat{p}_{iw}$, can be obtained by assuming $\eta$ follows normal distribution and estimating the resulting probit model using maximum likelihood. I also approximate the $G(.)$ function with a parametric function ($2^{nd}$ degree polynomial) of the region and size scores, normalized by the sum of the scores of all participating banks:
It is important to emphasize that the empirical strategy is robust to these particular
distributional and functional form assumptions. The probability model in (II-6) is estimated to
construct an instrument for bank loanable funds in (I-2) and (IV-2). Following Wooldridge
(2002), the 2SLS estimates of the parameters in (I-2) and (IV-2) will converge asymptotically
to the true parameter even if (II-6) is misspecified. In an unreported robustness check, I
estimated (II-6) using a linear probability model with bank fixed effects and the results that
will be presented in the next section remained unaltered.

The region and size point scores do not vary by wave in (II-7). The scores corresponding
to the first time the banks are observed in the sample are used to avoid the potential bias
introduced by banks gaming the allocation formula. Since bank expected profits in (II-5) are
increasing in the region and loan size scores, banks could manipulate loan size and regional
distributions to increase their share of program resources. This problem is avoided by not
allowing the scores vary in time. As a result, all the time series variation in the predicted
participation is induced by changes in wave size.

I then use $\hat{p}_w$ to estimate the expected cash windfalls, by modifying the formula for actual
cash windfalls given in (II-4). Actual cash windfalls, $C_{iw}$, depend on the sum of the region and
size scores of the actual participating banks. Instead I use the sum of the characteristics of all
banks (participating and non-participating) weighted by the predicted probability of
participation ($\hat{p}_w$). Using this expected sum in (II-4) gives the expected cash windfall to bank $i$
conditional on participation in wave $w$:11

$$\hat{C}_{iw} = A_w \left( \frac{Z_{region_i}}{2 \cdot \sum_j \hat{p}_w Z_{region_j}} + \frac{Z_{size_i}}{2 \cdot \sum_j \hat{p}_w Z_{size_j}} \right)$$  \hfill (II-8)

The last two rows of Table 1 show the descriptive statistics of the resulting expected cash
windfalls variable, in levels and as a proportion of loans outstanding. Expected cash windfalls
are about 7.6% of the stock of loans of participating banks during the sample period. A
regression of actual cash windfalls on predicted cash windfalls, bank and month fixed effects
indicates that the coefficient on predicted cash windfalls is close to one and statistically significant. This indicates that expected financing is a good proxy for actual financing both in the time series and cross section, and that the cross sectional allocation rule (II-4) was strictly enforced.

C. Testing the Identifying Assumptions

Two identification assumptions must be satisfied for expected cash windfalls to be a valid instrument for bank liquidity in specification (I-2). First, that cash windfalls did not change the marginal cost of financing. I previously argued that even though program financing was subsidized, it was available in limited amounts and banks held at all times liabilities at the market rate (program financing was infra-marginal). A somewhat starker assumption is that, because the additional liquidity provided by the program was small relative to bank assets, cash windfalls did not change the risk profile of the banks and thus did not affect the cost of capital. To test this assumption, I look at how the interbank interest rate and the interest rate on subordinated debt that banks face change when they receive cash windfalls. These rates proxy for the short and medium term cost of borrowing of banks, and we would expect them to be negatively correlated with cash windfalls if the program affected significantly the risk profile of the participating banks.  

The estimated coefficients of a regression of changes in interest rates on changes in cash windfalls, bank and month fixed effects are shown in Table 2. Both actual and expected cash windfalls are used as a right hand side variable and the bank sample is reduced to those that received cash windfalls at any time between 1993 and 1999. Even though the point estimates are negative as expected when actual cash windfalls are used, these are not statistically distinguishable from zero. Moreover, the coefficients become positive (but insignificant) when interest rates are regressed on expected cash windfalls. The results in this table corroborate that if lending changes due to the cash windfalls, it is not because the marginal cost of capital of the banks was affected by the change in liquidity.

The second identifying assumption, mentioned in the last subsection, is that the expected cash windfalls variable is uncorrelated with other sources of changes in bank liquidity or lending opportunities. I test this second assumption by looking at the correlation between expected cash windfalls and proxies for bank liquidity needs and investment opportunities. I
use lagged changes in bank deposits and lagged bank cash flows as these proxies. A decline in
bank deposits will first create a liquidity shortage and might be correlated with the
expectations depositors have of the profitability of investment of the bank. And as in non-
financial firms (Kaplan and Zingales 1997; Alti 2003; Moyen 2004), cash flows are potentially
correlated with investment opportunities.¹³

Table 3 shows the estimated coefficients of a regression of cash windfalls, actual and
expected, on lagged changes in deposits, lagged cash flows, and bank and month fixed effects.
The estimation using actual cash windfalls serves as a benchmark of what to expect when a
variable is correlated to liquidity needs and investment opportunities. In fact, we expect that
bank participation in the program will be motivated, at least in part, by liquidity needs and
potentially profitable investments. If so, actual cash windfalls should be negatively correlated
to lags of the deposit growth and positively correlated with lags of cash flows. Column 1
shows that actual cash windfalls were in fact negatively and significantly correlated with lagged
shocks to deposits (2 and 4 lags). There is also a positive but not significant correlation
between lagged cash flows and actual cash windfalls. These results suggest that bank
participation in the program was significantly motivated by liquidity shortages.

The same correlation is not present when the expected cash windfalls variable is used
instead (columns 2 and 3 of Table 3), neither within the sample of banks that participated in
the program or in the entire sample of banks. Expected windfalls are not significantly related
to the proxies of either liquidity shocks or changes in investment opportunities. These results
corroborate that the expected cash windfalls variable is a suitable candidate as an instrument
for bank liquidity.

III. Data Sources and Descriptive Statistics

The data for this paper is obtained from three sources. First, I use monthly balance sheets
and earnings reports for all the banks in the Argentine financial system between January 1995
and December 2001. All banks and depository institutions are required to provide this
information on a monthly basis to the banking regulatory agency in the Central Bank of
Argentina. Each observation in this database consists of fully detailed financial statements for
bank i at month t. The descriptive statistics of selected variables from the financial statements

16
are shown in column 1 of Table 1. These statistics are constructed first averaging each variable across monthly observations between January 1998 and December 2000, which will be the sample period for the preferred estimations in the paper. The means and standard deviations are then calculated over the resulting cross section of banks (excluding government owned banks).

The average bank held $1.1 billion in assets during the sample period. The important presence of large, foreign owned banks drives much of this statistic. While foreign banks hold almost half of the assets on the banking system and each has on average $3.1 billion in assets, local banks are considerably smaller ($0.7 billion in assets, see column 2 of Table 1). Only local banks received cash windfalls from the MYPES program. Thus, all the estimates that result from the empirical strategy described in the previous section will be valid for this subset of banks.

The second source of data is the Public Credit Registry database, or CDSF for its acronym in Spanish. Each observation in this database represents a loan, credit line or credit commitment \( j \), issued to firm \( k \) by bank \( i \) at month \( t \). I will use indicators \( i, j, k \) and \( t \) consistently along the paper to indicate bank, loans, firm, and months respectively. Both firms and banks have unique tax code identifiers that allow constructing a panel dataset, and also linking the CDSF data with the bank financial statements. The CDSF contains monthly data on all firms or individuals with more than $50 of debt with a financial institution in Argentina. For every loan, the database includes debtor ID number, the issuing bank ID number, the principal outstanding, the amount and type of collateral posted and a code describing the repayment situation. The repayment situation code ranges from 1 to 6, where 1 represents a good standing loan and 5 and 6 represent defaulted loans. The categories are precisely defined in terms of the days behind in payment, debt refinancing and bankruptcy filings.\(^{14}\)

I use this dataset to reconstruct the actual performance of every loan and the credit history of every borrower. A loan originated at time \( t \) can be observed at time \( t+T \) and its repayment status assessed. In a similar fashion, a firm that received a loan at time \( t \) can be observed at time \( t+T \) to assess whether is has defaulted in that loan, in all its loans or filed for bankruptcy. This assures that the performance measures are in fact linked to the incremental (marginal) investments of banks during cash windfalls. Finally, it is important to note that the CDSF
reports both loans and credit lines, but these cannot be distinguished from each other in the data. Thus, firm level variables constructed with the debt reported in the CDSF measure total available credit and not actual bank debt usage or leverage.

I choose to limit $T$ to 24 months to avoid censoring due to data limitations (the CDSF data is not available during year 2002 and loans issued in December 1999 can be followed up to 24 months). To check whether this limit introduces a substantial measurement error of default rates, I estimate the monthly hazard function of the default rate—the probability that a loan issued at month $t$ defaults at month $t+T$, conditional on not having defaulted at $t+T-1$. The kernel estimation, plotted in Figure 3, is performed over the sub-sample of loans in the CDSF with at least three years of observable repayment history (issued between January and August 1998). The plot shows that the hazard rate peaks before 12 months, and the cumulative hazards indicate that 85% (45%) of the loans that default, do so within 24 (12) months of being issued. This indicates that the chosen windows capture a substantial fraction of the loan defaults and do not introduce substantial measurement error.

Column 1 of Table 4 shows the descriptive statistics of all the loans, credit commitments, and credit line expansions (from now on called loans for conciseness) issued between January 1998 and December 1999. There were 750,526 loans issued to 222,146 firms or individuals. The average loan had a principal of $16,691 and 12.3% of this principal was secured with collateral. Regarding loan performance, 16.8% of all the loans were defaulted within 24 months after being issued. Loan recipients had on average $58,551 in existing bank debt, and 14.1% of the loans were issued to borrowers with some non-performing debt in their repayment histories.

The third source of data is the MYPES database, collected and managed by the Ministry of Economy in Argentina. This database is used to obtain information on the timing, size and across bank allocation of the financing provided by the program to financial institutions. The database holds information on the firms that received the program loans and the characteristics of these loans, such as date of initiation, principal, duration, grace period, and interest rate (see descriptive statistics in Table 5).
IV. Results

I now proceed to present the main results of the paper. The first subsection shows there is a substantial correlation between cash windfalls and bank loanable funds (first stage). The second presents the 2SLS estimates of the sensitivity of lending to liquidity and replicates the estimates of this sensitivity in the existing literature. The next two subsections look at the effect of the liquidity shock on loan portfolio performance and on borrower outcomes. Finally, I present several specification and robustness checks.

A. The Effect of Cash Windfalls on Loanable Funds (First Stage)

Before proceeding to the results of interest, we must verify that expected cash windfalls in fact had a significant impact on the loanable funds of the bank. This is a necessary condition for the 2SLS specification in (1-2) to work, and can be tested by estimating the following first stage regression:  

\[ \ln F_{it} - \ln F_{it-1} = \alpha_i + \alpha_t + \phi (\ln \hat{p}_i \hat{C}_{it} - \ln \hat{p}_i \hat{C}_{it-1}) + \eta_{it} \]  

This first stage is a regression of loanable funds on expected cash windfalls (in growth rates) and bank and month fixed effects ($\alpha_i$, $\alpha_t$). Bank fixed effects assure that all bank specific effects on outcomes are controlled for, since the results are derived from the within bank time series variation of liquidity. That is, I will be comparing outcomes of bank $i$ at time $t$, when a cash windfall occurs, to loans issued by banks $i$ at time $t-1$ and $t+1$. Month fixed effects allow controlling for all month specific factors that affect the entire cross section of banks.

Panel 1 of Table 6 shows the results of the of the first stage estimation. The estimated $\phi$ is 0.068 (Std. Dev.=0.021), so there is a positive and significant relationship between cash windfalls and bank liquidity in the entire bank sample (column 1). Given the average loanable funds, expected cash windfalls and predicted probability of participation of banks in the sample, this elasticity implies that on average bank loanable funds increased by $1 for every dollar of program financing received. This point estimate indicates that banks did not use the cash windfalls provided by program financing to substitute for other existing sources of finance. It also implies that cash windfalls had a strong influence on the financial position of banks that can be used to test for financing constraints.
B. Test of Financing Frictions: Sensitivity of Lending to Bank Liquidity

Baseline Result

I use specification (1-2) to obtain the 2SLS estimate of the sensitivity of lending to changes in bank loanable funds, $\beta_0$, exploiting expected cash windfalls as source of variation in the financial position of banks. Table 7 shows the OLS and 2SLS estimates of $\beta_0$ using the sample period that includes the final four waves of the program. I discuss here the preferred results using the entire sample of banks (columns 1 through 5), and differ the discussion about the results using alternative sub-samples to the end of the section.

The estimated sensitivity of lending to changes in loanable funds is 0.745 (Std. Dev. 0.139). The standard errors are heteroscedasticity robust and allow for clustering at the bank level, and the estimate is significantly different from zero. This means that the null hypothesis of no financing frictions ($\beta_0=0$) is rejected and that shocks to the financial position of banks affect their ability to issue loans. The lending response to a change in liquidity is substantial: the estimated elasticity implies that loans increase by $0.66$ for every dollar of additional liquidity (calculated at the average loans and loanable funds in the sample).

The standard errors also allow rejecting that banks lent out $1$ of every dollar of extra liquidity. Given that the liquidity provided by cash windfalls had no legal reserve requirements, this result implies that banks chose to allocate a fraction of the additional resources in other liquid assets (cash, bonds, and et cetera).\textsuperscript{16} This behavior is consistent with an optimal portfolio allocation under asymmetric information and liquidity risk (as in Stein 1998). The point estimate suggests that banks allocate a third of every dollar of additional liquidity to assets other than loans, which is smaller than the average in the sample (average loan to asset ratio of 0.5).

Comparison to the Literature

The result that lending is sensitive to cash windfalls is in line with the original results by Bernanke and Blinder (1988) and others that used deposits as the source of variation of bank liquidity. Critics to their work argued that the observed correlation between lending and liquidity could be due to an upward bias introduced by the endogeneity of deposits. I repeated the estimations of Table 7 using deposits as an instrument for loanable funds, and obtained estimates for $\beta_0$ that are not statistically different from the OLS ones, which are downward
biased (0.314). This corroborates the findings of Bernanke and Blinder and suggests that previous research that uses deposits as a source of variation in bank liquidity might have underestimated the sensitivity of lending to the financial position of banks.

Kashyap and Stein (2000) and subsequent work argue that the sensitivity of lending to liquidity shocks will be higher for banks that are more constrained. To verify this I estimate the following variation of specification (I-2):

\[
\ln L_{it} - \ln L_{it-1} = \alpha_i + \alpha_t + \beta_0(\ln F_{it} - \ln F_{it-1}) + \beta_1(\ln F_{it} - \ln F_{it-1}) ConstrainedBank_i + \varepsilon_{it} \quad (IV-2)
\]

where \( ConstrainedBank_i \) is a dummy equal to one if a bank is constrained according to observable bank characteristics. Larger (Kashyap and Stein 2000) and more capitalized (Kishan and Opiela 2000) banks are presumed to be less constrained in their access to financing. Thus, \( ConstrainedBank_i \) will be set to zero for banks in the top quartile of the assets and capitalization distributions, depending on the specification. The parameter of interest, \( \beta_1 \), represents the difference in the sensitivity of lending to liquidity of the sub-set of constrained banks (e.g. small) relative to the unconstrained ones (e.g. large).

The results of the estimation across banks of different size and capitalization are reported in columns (3) and (4) of Table 7. The point estimates of \( \beta_1 \) in both specifications are positive, which is consistent with smaller and less capitalized banks having a larger sensitivity of lending to changes in bank liquidity. However, neither of the estimates is statistically significant. The magnitude of the cross sectional variation appears to be small relative to its level: the point estimates indicate that small banks have a lending sensitivity of 0.70 while large ones have an estimated sensitivity of 0.69.

This result may be in part driven by the fact that specification (IV-2) compares large and small banks within the group of banks that received cash windfalls, which are constrained according to the estimates from specification (IV-1). This means that within the group of constrained banks, size and capitalizations are not very good predictors of the sensitivity of lending to liquidity. It also suggests that the cross sectional comparison approach could underestimate the magnitude of this sensitivity when all banks are constrained. It would lead, for example, to underestimate the magnitude of the impact of monetary policy on the supply of credit by small, local banks and its potential effects on the availability of credit by smaller businesses, an issue that I explore further below.
C. Financing Constraints or Free Cash Flows?

The effects of financing frictions faced by banks on real outcomes and investment are theoretically ambiguous. On the one hand, financial frictions may arise endogenously as a consequence of an agency problem between the providers of finance and bank managers. For example, limited financing may prevent empire-building bank managers from over investing (Jensen 1986; Stulz 1990; Hart and Moore 1995), in which case cash windfalls would finance unprofitable loans or investments. On the other hand, financial constraints may be inefficient in the sense that they prevent banks from investing in profitable loans (Stein 1998).

The different empirical predictions of the two models can be tested using the loan level data available for this paper. I first look at whether the loans issued during the cash windfalls are significantly riskier (more likely to default) than loans issued by banks in other periods using the following specification:

\[
Default_{ijt} = \alpha_i + \alpha_t + \alpha_s + \psi_t Windfall_{it} + \omega_{ijt}
\]  
(IV-3)

Each observation is a loan \(j\) issued by bank \(i\) at time \(t\). \(Default_{ijt}\) is a dummy equal to one if loan \(j\) defaults between \(t\) and \(t+T\), where \(T\) will be set to 12 or 24 months. \(Windfall_{it}\) is a dummy equal to one if bank \(i\) receives a cash windfall at time \(t\). I will use the predicted probability of participation estimated in section II.B, \(\hat{p}_n\), as an instrument for \(Windfall_{it}\) to estimate \(\psi_t\) using 2SLS. Since cash windfalls vary at the bank level, \(\psi_t\) can be interpreted as the change in the default rate of loans during liquidity expansions. The sector fixed effects (\(\alpha_s\)) account for the potential differences in the sector composition of the loan portfolios of different banks. Also, all standard errors are estimated allowing for clustering at the bank level.

The estimated effects of cash windfalls on loan default rates, shown in panel 1 of Table 8, are \(\psi_{12}=-0.004\) and \(\psi_{24}=-0.009\) and neither is statistically different from zero. These estimates suggest that banks expanded lending with no significant effect on the quality of their loan portfolios, which is inconsistent with the free cash flows interpretation. Given the magnitude of the lending expansion (4% of total loans for the average program bank), finding no effect on the subsequent default rates of these loans suggests that banks were severely constrained before receiving cash windfalls.\(^{17}\)
D. Effect on Firm Access to Credit and Probability of Bankruptcy

An alternative approach to ascertain the economic relevance of financial constraints at the bank level is to assess the impact of cash windfalls on borrower outcomes. Even if a bank is constrained and cannot finance all profitable lending opportunities, investment will not be affected if firms may borrow from other sources, including unconstrained banks. On the contrary, if banks are constrained and firms cannot easily substitute financing sources, an improvement in the financial position of a bank should lead to an improvement in the financial position of its borrowers. To test this hypothesis I look at whether borrowers’ total availability of bank credit and probability of bankruptcy changes when their lender institutions receive cash windfalls using the following specifications:

\[
\ln(\text{Debt}_{kt}) - \ln(\text{Debt}_{kt-1}) = \alpha_k + \alpha_t + \chi \text{LenderWindfall}_{kt} + \nu_{kt} \tag{IV-4} \\
\text{Bankrupt24}_{kt} = \alpha_k + \alpha_t + \chi \text{LenderWindfall}_{kt} + \nu_{kt} \tag{IV-5}
\]

Each observation corresponds to a firm \( k \) that received a loan at time \( t \) in the sample period. \( \text{Debt}_{kt} \) is the total bank debt of firm \( k \) aggregated across all banks at the time of receiving the loan. \( \text{Bankrupt24}_{kt} \) is a dummy equal to one if firm \( k \) filed for bankruptcy between \( t+1 \) and \( t+24 \). The independent variable of interest, \( \text{LenderWindfall}_{kt} \), is a dummy equal to one if firm \( k \) obtained a loan from a bank that received a cash windfall at time \( t \). As in (IV-3), I use the predicted probability of bank participation in the program as an instrument for \( \text{LenderWindfall}_{kt} \) to estimate \( \chi \) using 2SLS. Finally, \( \alpha_k \) and \( \alpha_t \) are firm and month fixed effects.

The firm fixed effects estimation of \( \chi \) is derived from the within firm variation of bank credit and bankruptcy. It compares the outcomes of a firm that obtains a loan from a bank that received a cash windfall with the same firm when it receives a loan from a bank that did not.\(^{18}\) This specification has the advantage of controlling for all firm specific characteristics and of avoiding biases introduced by changes in the composition of loan recipient selection during cash windfalls. As in previous specifications, the instrumental variables approach deals with bank level selection.

Table 9 shows that the estimated \( \chi \) using specification (IV-4) is 0.077 and using specification (IV-5) is -0.006 (columns 1 and 3). Both estimates are statistically significant using robust standard errors clustered at the borrower level.\(^{19}\) These estimates imply that
borrowing from a bank that received a cash windfall results in a 7.7% increase in total available bank finance and a 0.6 percentage point decrease in the probability of default. Cash windfalls and the subsequent expansion of bank credit improved the availability of credit and the probability of survival of borrowers. These results are consistent with banks being financially constrained and suggest that these constraints have an important impact in the financial position of their borrowers.

The observed increase in available credit together with a decrease in the probability of bankruptcy suggests that bank borrowers were also financially constrained before their lenders received the cash windfalls. Additional evidence in support of this claim can be drawn from looking at how the estimated effect varies across firms that differ in their dependence on external finance. When firms are financially constrained, the impact of a shock to the financial position of the lender should increase as the firm relies more heavily on external finance. To check this I include in specifications (IV-4) and (IV-5) an interaction between the \( \text{LenderWindfall}_{kt} \) variable and a dummy equal to one if a firm belongs to an industry that is highly dependent on external finance according to the industry classification in Rajan and Zingales (1998). As expected, the results indicate that firms that rely more heavily on external finance experience a larger decline in their probabilities of bankruptcy when their lender receives a cash windfall (column 4). This evidence is consistent with the hypothesis that firms were financially constrained.

E. Additional Identification and Robustness Tests

The Instrument is Not Correlated with Investment Opportunities

Khwaja and Mian (2005) propose an alternative way to test whether the results are biased due to changes in investment opportunities of the bank using the following firm fixed effects specification:\textsuperscript{30}

\[
\ln(\text{Debt}_{ikt}) - \ln(\text{Debt}_{ikt-1}) = \alpha_k + \alpha_i + \alpha_t + \rho (\ln \hat{p}_{ikt} \hat{C}_{ikt} - \ln \hat{p}_{ikt-1} \hat{C}_{ikt-1}) + \omega_{ikt}
\] (IV-6)

Each observation in this specification is a bank-borrower-month cell (sub indexes \( i, k \) and \( t \)). The dependent variable is the change in log debt of firm \( k \) with bank \( i \) at month \( t \), and the independent variable of interest is the expected cash windfalls variable. The test consists in comparing the estimation of \( \rho \), with and without the inclusion of the firm fixed effect \( \alpha_k \) (firm FE and OLS estimations respectively). Under the null hypothesis that the liquidity shock is
uncorrelated with bank investment opportunities, the FE and the OLS estimates are equal. Using deposits as the source of variation in bank liquidity, Khwaja and Mian find that the OLS estimate is biased downwards.

The OLS and the FE estimates of $\rho$ in (IV-6) using the expected financing variable are 0.0035 and 0.0034 respectively (Columns 1 and 2 of Table 10). Both estimates are significantly different from zero, but more importantly, the estimates are statistically indistinguishable from each other. This implies that the estimated effects of expected cash windfalls on bank lending are not driven by changes in bank investment opportunities.

The First Stage is Not Driven by Aggregate Variations in Credit Demand or Supply

The reason we observe a correlation between expected cash windfalls and the financial position of banks could be driven by some economy-wide and unaccounted for variable affecting the lending behavior of all banks. I use a variation of the first stage specification (IV-1) to rule out this possibility. If expected cash windfalls are uncorrelated to aggregate factors influencing the credit market, this variable should only explain variations in the financial position of banks that were likely to receive program financing. I divide the sample between banks with a high and a low average predicted probability of participation in the program. Banks are defined as having a high average probability of participation if they are in the top quartile of the distribution estimated participation probabilities, $\hat{p}$. The estimated $\phi$ in each sub-sample is shown in columns 2 and 3 of Table 6. Expected cash windfalls have a positive and significant effect on the liquidity of banks with a high probability of participation in the program, and no effect on low-probability of participation banks. Thus, the observed correlation between expected cash windfalls and bank liquidity is not driven by aggregate factors beyond those captured by the month fixed effects.

The 2SLS Estimates are Not Driven by Bank Selection

All the bank level 2SLS estimates in this paper include bank fixed effects. This means that estimations are derived from within bank variations in liquidity. As long as the identification assumptions regarding the exogeneity of the instrument are valid, the estimated parameters should be robust bank sub-sample selection. To check this I perform the 2SLS estimation of the sensitivity of bank lending to changes in loanable funds of subsection B, but restricting the sample of banks to those that participated at least once in the program, and excluding all
banks that participated in every wave. This excludes every bank that did not experience within bank variation in liquidity during the sample period due to the cash windfalls. The estimated $\beta_0$, performed over a sample of 26 banks and 964 observations, is 0.66 with a standard error of 0.29, which is statistically indistinguishable from the estimate using the entire bank sample (Column 7, Table 7).

**Loan Commitments**

I repeat the estimation of the sensitivity of lending to liquidity of subsection B using as the dependent variable total loan commitments instead of loans outstanding. Total commitments are calculated aggregating the amounts reported in the CDSF at the bank-month level. This estimation provides a robustness check on the results regarding the sensitivity of lending to liquidity to the data used and on the accuracy of the CDSF data. The estimated sensitivity for the reduced sub-sample of banks is 0.895 and significant at the 10% level (column 6 of Table 7). The point estimate of the sensitivity of loan commitments is larger than the sensitivity of loans (0.66), although the difference is not statistically different. The point estimate is suggestive that banks expand not only lending but also expand credit lines and other commitments when they receive a positive liquidity shock.

**V. Why Are Firms Constrained?**

Why is it that when liquidity constrained banks are prevented from taking all profitable lending opportunities, unconstrained banks or other providers of finance do not step up and fill the gap? One hypothesis is that all providers of finance are equally constrained during the sample period [aggregate liquidity constraints as in Holmstrom and Tirole (2002) or Caballero and Krishnamurthy (2004)]. But the significant share of large, foreign owned banks in the market suggests that some financial intermediaries were not obviously constrained.

An alternative hypothesis is that there are frictions preventing borrowers from switching between providers of finance. These frictions may arise when lenders obtain private information about the creditworthiness of their borrowers through the lending relationship, and competing uniformed lenders face adverse selection and a potential winner’s curse when attempting to bid a borrower away from the informed bank. The theory on lending relationships, as in Rajan (1992) and Von Thadden (2004), suggests a testable implication that
can be verified empirically with the data available to this paper. Namely, that uninformed lenders are reluctant to extend credit to borrowers that are switching from an informed sources of finance, and attract borrowers of a low average quality when they do so.

The descriptive statistics of the loans classified by type of loan recipient in Table 4 are consistent with this implication. Less than 5.5% of the loans issued to borrowers with no pre-existing relationship with the issuing bank (new borrowers, column 3), go to borrowers that have had some debt with another financial institution within the last 6 months (switching borrowers, column 4). Also, the average switching loan recipient appears to be of a much better quality from an ex ante point of view, than the average loan recipient with a credit history in the issuing bank (existing borrower, column 2): 5.7% of switching borrowers have some non-performing debt at the time of receiving the loan, versus 14.1% of existing borrowers. Nevertheless, loans to switching borrowers are two times more likely to default.

Additional evidence can be drawn from exploiting the empirical setting provided by the cash windfalls to look at the default probability of the marginal loan to existing, new and switching borrowers. In panels 2 through 4 of Table 8 I show the results of estimating specification (IV-3) using the sub-sample of loans issued to each type of borrower. Looking at the default rates after 12 months (Column 1), the estimates of $\psi_{12}$ for existing, new and switching borrowers are -0.002, 0.038 and 0.176 respectively. This implies that during cash windfalls the average default rate of switching borrowers increases more than four times as much as the average default rate of borrowers with no previous relationship with the bank or any credit history whatsoever. The results are even starker if we look at the default rates after 24 months in column 2. Both the reluctance of banks to lend to switching borrowers and the high default risk involved in doing so are consistent with the predictions of relationship lending models.

One alternate interpretation is that banks are deliberately choosing to lend to riskier borrowers. This does not appear to be the case when looking at the average past non-performing debt of loan recipients in Table 4. Corroborating evidence can be provided by looking at how the fraction of loan recipients with past non-performing debt changes during cash windfalls. I estimate specification (IV-3) again but using as the dependent variable a dummy equal to one if the loan recipient has some non-performing debt outstanding at the
time of receiving the loan. The estimated coefficients using the existing and the switching borrower sub-samples are 0.047 and 0.039, shown in column 3 of Table 8. Both estimates are statistically significant, but more importantly, they are not significantly different from each other. The fraction of loan recipients with a bad credit record increased in the same proportion for both existing and switching borrowers. Together with the fact that switching loan recipients have on average better past performances, the results indicate that the high default rate of marginal loans to switching borrowers was not readily predictable by observable measures of credit quality.

Finally, the fact that banks lend at all to new and switching borrowers when they can expand lending to safer existing ones is also consistent with the private information hypothesis. If banks have poor information about the quality of new borrowers but can obtain signals of this quality through a lending relationship, then lending to new borrowers can be interpreted as an investment in gathering information. As in Petersen and Rajan (1995), banks will be willing to face higher default rates in the short run because private information allows them to extract rents from their relationship borrowers in the future. In turn, competing banks will face a trade off between trying to attract these borrowers and capture part of the informational rents, and the probability of attracting the worst borrowers (winner’s curse). As a result some bids are made and switching happens in equilibrium (Broecker 1990; Rajan 1992; Von Thadden 2004).

VI. Conclusions

This paper provides evidence that exogenous shocks to the financial position of small banks have a substantial impact in their ability to issue loans. Banks expand loans by $0.66, and total loans plus loan commitments by $0.89, for every dollar of cash windfalls they receive from a government program. The estimated effect on lending can be solely attributed to the expansion in liquidity, since the expected cash windfalls were uncorrelated with changes in the marginal cost of capital, lending opportunities or other factors affecting the demand or supply of bank credit.

Then, using novel loan level data from a public credit bureau to construct the credit history of every borrower, I show that the ex-post performance of loans issued during cash windfalls
is no different from the performance of other loans issued by the bank. This suggests that the lending expansion is the result of liquidity constraints, and not of an agency problem that leads bank managers to over invest in poor quality loans.

The paper then shows that shocks to small bank liquidity also affect the financial position of their borrowers. When a firm’s lending bank receives a cash windfall, the firm’s total bank financing increases by 7.7% and its probability of becoming bankrupt declines by 0.6 percentage points. Moreover, the decline in the probability of bankruptcy is larger for firms that are more dependent on external finance. The results indicate that when banks are liquidity constrained, positive liquidity shocks at the bank level help alleviate financial constraints at the firm level.

Liquidity constraints of small banks affect firm outcomes in an environment where multinational holding banks accounted for almost 50% of the assets of the banking system. Firms were unable to substitute credit from constrained lenders with other sources of funds, even when there were other potentially unconstrained banks to supply credit. The last section of the paper documents how adverse selection in the bank credit market may be a key determinant of the low elasticity of substitution across sources of financing.

The findings on small bank liquidity constraints of this paper are likely to carry in various economic and institutional environments. High costs of switching lenders documented in the last section are prevalent in other banking markets [see evidence for the U.S. in Hubbard et al. (2002)]. Also, small banks in developed financial markets make little use of derivatives to reduce their exposure to liquidity risk even when these instruments are available to them [e.g. community banks in the U.S. (Sierra and Yeager 2004)]. These observations suggest that the link between the financial positions of small banks and their borrowers will hold more general settings.

The literature on the lending channel has emphasized the role of financial intermediaries in amplifying aggregate shocks to liquidity (Bernanke 1983; Bernanke and Blinder 1992). The results of this paper corroborate this role for small banks, and also suggest that even localized, bank specific liquidity shocks can have an effect on investment and firm outcomes.
VII. References


## VIII. Tables

### Table 1

**Bank Descriptive Statistics (Non-Government Banks), by Ownership and Program Participation (Thousands of $)**

Means and standard deviations (in brackets) are reported. The statistics are calculated for a sample of 111 banks (83 locally owned, 26 of which received cash windfalls from the program at some time between 1993 and 1999), first averaging each variable across all monthly observations between January 1998 and December 2000 (the preferred sample period) and then across banks. The reported standard errors are calculated from the cross-sectional variation. 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). Expected Cash Windfalls are calculated according to (II-8). Program banks hold on average 10.2%, and local banks 51% of the total assets of the banking system.

<table>
<thead>
<tr>
<th></th>
<th>All Banks</th>
<th>Locally Owned Banks</th>
<th>Program Banks</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
</tr>
<tr>
<td>Assets</td>
<td>1,095,287</td>
<td>693,538</td>
<td>543,985</td>
</tr>
<tr>
<td></td>
<td>[2,396,431]</td>
<td>[1,880,620]</td>
<td>[599,719]</td>
</tr>
<tr>
<td>Loans</td>
<td>536,344</td>
<td>362,000</td>
<td>283,790</td>
</tr>
<tr>
<td></td>
<td>[1,241,008]</td>
<td>[1,043,741]</td>
<td>[332,044]</td>
</tr>
<tr>
<td>Liabilities</td>
<td>979,350</td>
<td>605,314</td>
<td>488,200</td>
</tr>
<tr>
<td></td>
<td>[2,168,293]</td>
<td>[1,674,728]</td>
<td>[539,852]</td>
</tr>
<tr>
<td>Deposits</td>
<td>569,590</td>
<td>384,378</td>
<td>361,719</td>
</tr>
<tr>
<td></td>
<td>[1,331,549]</td>
<td>[1,122,679]</td>
<td>[407,961]</td>
</tr>
<tr>
<td>Loanable funds</td>
<td>616,099</td>
<td>399,500</td>
<td>382,853</td>
</tr>
<tr>
<td></td>
<td>[1,348,276]</td>
<td>[1,151,055]</td>
<td>[418,375]</td>
</tr>
<tr>
<td>Loans/Assets</td>
<td>0.500</td>
<td>0.517</td>
<td>0.500</td>
</tr>
<tr>
<td></td>
<td>[0.146]</td>
<td>[0.140]</td>
<td>[0.109]</td>
</tr>
<tr>
<td>Deposits/Assets</td>
<td>0.515</td>
<td>0.538</td>
<td>0.626</td>
</tr>
<tr>
<td></td>
<td>[0.194]</td>
<td>[0.189]</td>
<td>[0.124]</td>
</tr>
<tr>
<td>Equity/Assets</td>
<td>0.133</td>
<td>0.144</td>
<td>0.133</td>
</tr>
<tr>
<td></td>
<td>[0.135]</td>
<td>[0.141]</td>
<td>[0.130]</td>
</tr>
<tr>
<td>ROA</td>
<td>0.31%</td>
<td>0.26%</td>
<td>0.14%</td>
</tr>
<tr>
<td></td>
<td>[1.22]</td>
<td>[1.23%]</td>
<td>[1.12]</td>
</tr>
<tr>
<td>Financial Rev./Loans (%)</td>
<td>13.6%</td>
<td>14%</td>
<td>12.8%</td>
</tr>
<tr>
<td></td>
<td>[7.2]</td>
<td>[7.6%]</td>
<td>[2.4]</td>
</tr>
<tr>
<td>Exp. Cash Windfalls (C)</td>
<td>1,547.5</td>
<td>1,630.4</td>
<td>1,598.7</td>
</tr>
<tr>
<td></td>
<td>[494.9]</td>
<td>[482.4]</td>
<td>[429.2]</td>
</tr>
<tr>
<td>Exp. Cash Windfalls/Loans</td>
<td>0.068</td>
<td>0.068</td>
<td>0.076</td>
</tr>
<tr>
<td></td>
<td>[0.166]</td>
<td>[0.154]</td>
<td>[0.196]</td>
</tr>
</tbody>
</table>

Source: Monthly balance sheets and earning reports from the banking regulatory agency in the Central Bank of Argentina and own calculations.
Table 2

Regression of Changes in Inter-Bank Rate and Subordinated Debt Rate on Changes in Actual and Expected Cash Windfalls, and Bank/Month Fixed Effects

Each column presents estimated coefficients from a specification of the following form:

\[ R_{it} - R_{it-1} = \alpha_i + \alpha_t + \beta \ln(C_{it}/C_{it-1}) + \epsilon \]

Where \( R_i \) is either the inter-bank rate (columns 1 and 2) or the subordinated debt rate (columns 3 and 4) faced by bank \( i \) at time \( t \). The rate for each type of debt is calculated dividing the interest rate accrued (from the earnings report at month \( t \)) by the stock of debt (from the balance sheet at time \( t-1 \)). \( C_i \) is either actual (columns 1 and 3) or expected (columns 2 and 4) cash windfalls of bank \( i \) at time \( t \), and \( \alpha_i \) and \( \alpha_t \) are bank and month fixed effects. All estimations are performed on the reduced sample of banks that received cash windfalls at some time between 1993 and 1999.

<table>
<thead>
<tr>
<th>Dependent Variable</th>
<th>Inter-Bank Debt Rate</th>
<th>Subordinated Debt Rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>Actual Cash Windfalls (growth)</td>
<td>-0.074</td>
<td>-0.001</td>
</tr>
<tr>
<td></td>
<td>[0.358]</td>
<td>[0.003]</td>
</tr>
<tr>
<td>Expected Cash Windfalls (growth)</td>
<td>1.748</td>
<td>0.173</td>
</tr>
<tr>
<td></td>
<td>[17.42]</td>
<td>[0.321]</td>
</tr>
<tr>
<td>Bank/Month FE</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
<td>991</td>
<td>984</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.15</td>
<td>0.07</td>
</tr>
</tbody>
</table>

* significant at 10%; ** significant at 5%; *** significant at 1%. Heteroscedasticity-robust standard errors in brackets, clustered at the bank level. All specifications include a full set of bank and month dummies.
Table 3
Regression of Actual and Predicted Financing Expansion Growth on Past Deposit Growth,
Past Cash Flow and Bank/Month Fixed Effects

Each column presents estimated coefficients from a specification of the following form:

\[ \ln(C_t / C_{t-1}) = \alpha_i + \alpha_t + \beta_0 \ln(D_{t-1} / D_{t-2}) + \beta_1 \ln(D_{t-2} / D_{t-3}) + \beta_2 \ln(D_{t-3} / D_{t-4}) + \beta_3 \ln(D_{t-4} / D_{t-5}) + \gamma_0 \ln(CF_t / CF_{t-1}) + \gamma_1 \ln(CF_{t-1} / CF_{t-2}) + \gamma_2 \ln(CF_{t-2} / CF_{t-3}) + \gamma_3 \ln(CF_{t-3} / CF_{t-4}) + \gamma_4 \ln(CF_{t-4} / CF_{t-5}) + \epsilon_t \]

where \( C_t \) is either actual (column 1) or expected (columns 2 and 3) cash windfalls of bank \( i \) at time \( t \), \( D_t \) represents deposits, \( CF_t \) cash flows, and \( \alpha_i \) and \( \alpha_t \) are bank and month fixed effects. Column 2 presents the estimates using the reduced sample of banks that received cash windfalls at some time between 1993 and 1999.

<table>
<thead>
<tr>
<th>Actual Cash Windfalls</th>
<th>Expected Cash Windfalls (growth)</th>
</tr>
</thead>
<tbody>
<tr>
<td>(growth)</td>
<td>Program banks</td>
</tr>
<tr>
<td>DepositGrowth(_{t-1})</td>
<td>0.028</td>
</tr>
<tr>
<td></td>
<td>[0.049]</td>
</tr>
<tr>
<td>DepositGrowth(_{t-2})</td>
<td>-0.162***</td>
</tr>
<tr>
<td></td>
<td>[0.058]</td>
</tr>
<tr>
<td>DepositGrowth(_{t-3})</td>
<td>-0.094</td>
</tr>
<tr>
<td></td>
<td>[0.086]</td>
</tr>
<tr>
<td>DepositGrowth(_{t-4})</td>
<td>-0.111*</td>
</tr>
<tr>
<td></td>
<td>[0.055]</td>
</tr>
<tr>
<td>CashFlow(_{t-1})</td>
<td>0.00078</td>
</tr>
<tr>
<td></td>
<td>[0.00035]</td>
</tr>
<tr>
<td>CashFlow(_{t-2})</td>
<td>0.0033</td>
</tr>
<tr>
<td></td>
<td>[0.00035]</td>
</tr>
<tr>
<td>CashFlow(_{t-3})</td>
<td>0.0058</td>
</tr>
<tr>
<td></td>
<td>[0.00056]</td>
</tr>
<tr>
<td>CashFlow(_{t-4})</td>
<td>0.0049</td>
</tr>
<tr>
<td></td>
<td>[0.00071]</td>
</tr>
</tbody>
</table>

Bank/Month FE | Yes | Yes | Yes
Observations | 1001 | 1003 | 5818
R-squared | 0.31 | 0.85 | 0.88

* significant at 10%; ** significant at 5%; *** significant at 1%. Heteroscedasticity-robust standard errors in brackets, clustered at the bank level. All specifications include a full set of bank and month dummies.
Table 4
Loan and Loan Recipient Summary Statistics, by Borrower Type

Means and standard deviations (in brackets) are reported. Statistics are estimated using the January 1998 to December 2000 preferred sub-sample. Each observation corresponds to a new loan, loan commitment or increase in credit limit extended during the sample period. Loan amount represents the amount of the loan or credit availability expansion. 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. Total bank debt is the sum of the bank debt held by the loan recipient across all financial institutions. Past non-performing loan is a dummy equal to one if the loan recipient has any non-performing debt at the time of receiving the new loan. A loan recipient is classified as new if it has no previous credit with the issuing bank, and existing otherwise. Switching borrowers are new borrowers that have received credit from another financial institution within the previous 12 months of receiving the new loan.

<table>
<thead>
<tr>
<th></th>
<th>All</th>
<th>Existing Borrowers</th>
<th>New Borrowers - All</th>
<th>New Borrowers - Switching</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
</tr>
<tr>
<td>Number of Loans</td>
<td>750,526</td>
<td>620,325</td>
<td>130,201</td>
<td>5,488</td>
</tr>
</tbody>
</table>

1. **Loan Characteristics**

<table>
<thead>
<tr>
<th></th>
<th>All</th>
<th>Existing Borrowers</th>
<th>New Borrowers - All</th>
<th>New Borrowers - Switching</th>
</tr>
</thead>
<tbody>
<tr>
<td>Loan amount ($)</td>
<td>16,691</td>
<td>17,722</td>
<td>11,776</td>
<td>15,602</td>
</tr>
<tr>
<td></td>
<td>[226,660]</td>
<td>[218,790]</td>
<td>[260,858]</td>
<td>[326,867]</td>
</tr>
<tr>
<td>Collateral/Loan</td>
<td>0.123</td>
<td>0.124</td>
<td>0.118</td>
<td>0.129</td>
</tr>
<tr>
<td></td>
<td>[0.301]</td>
<td>[0.299]</td>
<td>[0.312]</td>
<td>[0.324]</td>
</tr>
</tbody>
</table>

2. **Loan Performance**

<table>
<thead>
<tr>
<th></th>
<th>All</th>
<th>Existing Borrowers</th>
<th>New Borrowers - All</th>
<th>New Borrowers - Switching</th>
</tr>
</thead>
<tbody>
<tr>
<td>Default after 12 months (yes=1)</td>
<td>0.122</td>
<td>0.104</td>
<td>0.191</td>
<td>0.206</td>
</tr>
<tr>
<td></td>
<td>[0.328]</td>
<td>[0.306]</td>
<td>[0.393]</td>
<td>[0.404]</td>
</tr>
<tr>
<td>Default after 24 months (yes=1)</td>
<td>0.168</td>
<td>0.153</td>
<td>0.228</td>
<td>0.254</td>
</tr>
<tr>
<td></td>
<td>[0.374]</td>
<td>[0.359]</td>
<td>[0.420]</td>
<td>[0.435]</td>
</tr>
</tbody>
</table>

3. **Borrower History**

<table>
<thead>
<tr>
<th></th>
<th>All</th>
<th>Existing Borrowers</th>
<th>New Borrowers - All</th>
<th>New Borrowers - Switching</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total bank debt</td>
<td>58,551</td>
<td>6,444</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>[601,468]</td>
<td>[258,200]</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Past non-performing loan (yes=1)</td>
<td>0.141</td>
<td>0.057</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>[0.348]</td>
<td>[0.231]</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Source: Public credit registry (CDSF) collected and managed by the banking regulatory agency in the Central Bank of Argentina.
The statistics are calculated over the universe of 12,192 MYPES program loans to firms. The cash windfalls received by banks had to be matched to loans to eligible firms (firms with less than 20 workers and less than $200,000 in sales). In practice, banks relabeled loans to existing borrowers as program loans circumventing the allocation rule. Nevertheless, the relabeled loans mostly complied with the limitations MYPES imposed on the terms of the program loans: maximum amount of $20,000, maximum duration of 36 months (not including grace period), and maximum grace period of 12 months.

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

Table 6

First Stage: Regression of Loanable Funds (Cash Windfall Dummy) on Expected Cash Windfalls (Predicted Probability of Participation) and Bank/Month Fixed Effects

Each column presents estimated coefficients from a specification of the form:

\[ Y_{it} = \alpha_i + \alpha_t + \phi (\ln \hat{p}_{it} \cdot \hat{C}_{it} - \ln \hat{p}_{it-1} \cdot \hat{C}_{it-1}) + \eta_{it} \]

where \( Y_{it} \) is either loanable fund growth (\( \ln F_{it} - \ln F_{it-1} \) with \( F_t \) are loanable funds) of bank \( i \) at time \( t \), or a dummy equal to one if bank \( i \) receives a cash windfall from the program at month \( t \) (Panels 1 and 2 respectively). Also, \( \hat{p}_{it} \) is the predicted probability of participation and \( \hat{C}_{it} \) the expected cash windfalls conditional on participation, both estimated according to (II-7) and (II-8) respectively, and \( \alpha_i \) and \( \alpha_t \) are bank and month fixed effects. All estimates are based on the sample months between January 1998 and December 2000, which includes the final four waves of the program. The sub-sample partition in columns 2 and 3 is selected according to the predicted probability of participation. Banks are defined as having a high average probability of participation if they are in the top quartile of the distribution estimated participation probabilities, \( \hat{p} \).

<table>
<thead>
<tr>
<th>Bank Sub-Sample:</th>
<th>All</th>
<th>High-Probability of Participation</th>
<th>Low-Probability of Participation</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
</tr>
<tr>
<td>1. Dependent Variable: Loanable Fund Growth</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Expected Cash</td>
<td>0.068***</td>
<td>0.067**</td>
<td>0.016</td>
</tr>
<tr>
<td>Windfalls Growth</td>
<td>[0.021]</td>
<td>[0.030]</td>
<td>[0.024]</td>
</tr>
<tr>
<td>Bank/Month FE</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
<td>4,654</td>
<td>1,405</td>
<td>3,493</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.07</td>
<td>0.06</td>
<td>0.04</td>
</tr>
<tr>
<td>2. Dependent Variable: Cash Windfall Dummy</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Predicted Probability of Participation</td>
<td>0.057***</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Bank/Month/Industry FE</td>
<td>Yes</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>750,533</td>
<td></td>
<td></td>
</tr>
<tr>
<td>R-squared</td>
<td>0.59</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

* significant at 10%; ** significant at 5%; *** significant at 1%. Heteroscedasticity-robust standard errors in brackets, clustered at the bank level. All specifications include a full set of bank and month dummies.
Table 7

OLS/2SLS Estimates of the Sensitivity of Loans to Bank Liquidity, by Bank Size and Capitalization (Bank/Month Fixed Effects)

Each column presents estimated coefficients from a specification of the form:

\[ \ln L_i - \ln L_{i-1} = \alpha_i + \alpha_t + \beta_0 (\ln F_{i-1} - \ln F_{i-2}) + \beta_1 (\ln F_{i-1} - \ln F_{i-2})ConstrainedBank_i + \epsilon_{it} \]

where \( L_i \) are loans of bank \( i \) at month \( t \) (from balance sheets) in specifications 1 through 5, and loan commitments (using CDSF data and aggregating at the bank-month level) in specification 6. \( F_i \) are loanable funds, and \( ConstrainedBank_i \) is a dummy equal to one if bank \( i \) is likely to be liquidity constrained according to some observable characteristic, and \( \alpha_i \) and \( \alpha_t \) are bank and month fixed effects. Specification 3 uses \( Small_i \), a dummy equal to one if the bank is in the lowest quartile of the asset distribution, and specification 4 uses \( LowCap_i \), a dummy equal to one if the bank is in the lowest quartile of the equity to assets ratio distribution. Both variables are pre-determined, calculated at the time the banks first appear in the sample. Of the program banks in the 1998-2000 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. The Two-Stage-Least-Squares (2SLS) estimates are obtained using the change in expected cash windfalls as an instrument for the change in bank loanable funds, and expected cash windfalls interacted with \( Small_i \) and \( LowCap_i \) as an instrument for the interaction term between loanable funds and the dummy variables. The first stage for all estimates is shown in Table 6. The reduced sample of specifications 5 and 6 includes only banks that received a cash windfall from the program at some time between 1993 and 1999, but that did not receive cash windfalls in all waves.

| Bank Sub-sample: All Reduced |
|-----------------------------|-----------------------------|
| Dependent Variable (growth): | Loans | Loan Commitments |
| Estimation: | OLS | 2SLS | 2SLS | 2SLS | 2SLS | 2SLS |
| (1) | (2) | (3) | (4) | (5) | (6) |
| Loanable Fund Growth | 0.314*** | 0.745*** | 0.692*** | 0.627*** | 0.661** | 0.895* |
| [0.090] | [0.139] | [0.145] | [0.147] | [0.291] | [0.517] |
| Loanable Fund Gr. x Small | 0.012 | | | | |
| [0.221] | | | | | |
| Loanable Fund Gr. x LowCap | 0.063 | | | | |
| | | | | | |
| Bank/Month FE | Yes | Yes | Yes | Yes | Yes | Yes |
| # Banks | 113 | 113 | 113 | 113 | 26 | 26 |
| Observations | 4,654 | 4,654 | 4,654 | 4,654 | 964 | 964 |
| R-squared | 0.17 | | | | | |

* significant at 10%; ** significant at 5%; *** significant at 1%. Heteroscedasticity-robust standard errors in brackets, clustered at the bank level. All specifications include a full set of bank and month dummies.
Table 8

Bank Liquidity and Loan Risk – IV Estimates of Loan Default Rate on Liquidity Expansion Dummy including Bank/Month/Industry Fixed Effects

Each column presents estimated coefficients from a specification of the form:

\[ \text{Default}_{ijt} = \alpha_i + \alpha_t + \alpha_s + \psi \text{Windfall}_{it} + \omega_{ijt} \]

where each observation corresponds to a loan issued by bank \( i \) at month \( t \). \( \text{Default}_{ijt} \) is a dummy equal to one if loan \( j \) is non-performing (at least six months late, defaulted or the loan recipient has filed for bankruptcy) at some time between time \( t \) and time \( t+T \), where \( T \) can be 12 or 24 months (specifications 1 and 2 respectively). Specification 3 uses as the dependent variable a dummy equal to one if the loan recipient has some non-performing debt outstanding with any financial institution at time \( t-1 \). Windfall is a dummy equal to one if bank \( i \) receives a cash windfall from the MYPES program at time \( t \), where cash windfall months are defined as the three months that follow the date a program wave begins. Finally, \( \alpha_i, \alpha_t \) and \( \alpha_s \) are bank, month and loan recipient sector (3 digit industry sector) fixed effects. The Two-Stage-Least-Squares (2SLS) estimates are obtained using the change in predicted probability of participation as an instrument for the cash windfall dummy.

<table>
<thead>
<tr>
<th>Loan Non-Performing After:</th>
<th>Past Non-Performing Debt</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>12 months</td>
</tr>
<tr>
<td></td>
<td></td>
</tr>
<tr>
<td>1. All Loans</td>
<td></td>
</tr>
<tr>
<td>Liquidity expansion bank-month</td>
<td>-0.004</td>
</tr>
<tr>
<td>Observations</td>
<td>750,563</td>
</tr>
<tr>
<td>2. Existing Borrowers</td>
<td></td>
</tr>
<tr>
<td>Liquidity expansion bank-month</td>
<td>-0.002</td>
</tr>
<tr>
<td>Observations</td>
<td>620,325</td>
</tr>
<tr>
<td>3. New Borrowers</td>
<td></td>
</tr>
<tr>
<td>Liquidity expansion bank-month</td>
<td>0.038**</td>
</tr>
<tr>
<td>Observations</td>
<td>130,201</td>
</tr>
<tr>
<td>4. Switching Borrowers</td>
<td></td>
</tr>
<tr>
<td>Liquidity expansion bank-month</td>
<td>0.176**</td>
</tr>
<tr>
<td>Observations</td>
<td>5,488</td>
</tr>
</tbody>
</table>

* significant at 10%; ** significant at 5%; *** significant at 1%. Heteroscedasticity-robust standard errors in brackets, clustered at the bank level. All specifications include a full set of bank, sector and month dummies.
Table 9
Effect on Borrower Bank Credit and Bankruptcy: 2SLS Estimation of the Effect of a Cash Windfall on a Firm Lender on Total Bank Debt and Probability of Bankruptcy Including Borrower/Month Fixed Effects

Each column presents estimated coefficients from a specification of the form:

\[ Y_{kt} = \alpha_k + \alpha_t + \chi LenderWindfall_{kt} + \chi LenderWindfall_{kt} \cdot EFDependentFirm_{kt} + \nu_{kt} \]

where \( Y_{kt} \) represents an outcome of firm \( k \) at month \( t \), and each observation corresponds to a firm that received a loan at time \( t \). \( Y_{kt} \) is the change in log total bank debt in column 1 \([\ln(Debt_{kt}) - \ln(Debt_{kt-1})]\), and a dummy equal to one if the firm files for bankruptcy at some time between \( t \) and \( t+24 \) in column 2 \([Bankrupt24_{kt}]\). \( LenderWindfall_{kt} \) is a dummy equal to one if firm \( k \) received a loan at time \( t \) from a bank that received a cash windfall, and \( \alpha_k \) and \( \alpha_t \) are firm and month fixed effects. \( EFDependentFirm_{kt} \) is a dummy equal to one if a firm \( k \) is in an industry in the top quartile of the distribution of the external dependence index in Rajan and Zingales (1998). The firm fixed effects imply that the sample is reduced to borrowers that received more than one credit during the sample period (123,155 borrowers out of the original sample of 222,124). Also, all individuals are excluded from the sample.

<table>
<thead>
<tr>
<th>Dependent Variable</th>
<th>Change in Total Bank Debt</th>
<th>Probability of Bankruptcy</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>LenderWindfall</td>
<td>0.077***</td>
<td>0.076***</td>
</tr>
<tr>
<td></td>
<td>[0.007]</td>
<td>[0.007]</td>
</tr>
<tr>
<td>LenderWindfall x EFDependentFirm</td>
<td>0.001</td>
<td></td>
</tr>
<tr>
<td></td>
<td>[0.001]</td>
<td></td>
</tr>
<tr>
<td>Borrower/Month FE</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
<td>411,468</td>
<td>411,468</td>
</tr>
</tbody>
</table>

* significant at 10%; ** significant at 5%; *** significant at 1%. Heteroscedasticity-robust standard errors in brackets, clustered at the borrower level. All specifications include a full set of borrower and month dummies.
Table 10

**Effect on Borrower Bank Credit: OLS and FE estimations of the Reduced Form of Change in Bank Debt on Changes in Expected Cash Windfalls**

Each column presents estimated coefficients from a specification of the form:

\[ \ln(\text{Debt}_{kt}) - \ln(\text{Debt}_{kt-1}) = \alpha_k + \alpha_i + \alpha_t + \rho (\ln \hat{p} \hat{C}_{ikt} - \ln \hat{p} \hat{C}_{ikt-1}) + \nu_{ikt} \]

where the left-hand-side variable is the debt growth of firm \( k \) with bank \( i \) at month \( t \). On the right hand side, \( \hat{p} \hat{C}_{ikt} \) are expected cash windfalls, and \( \alpha_k, \alpha_i, \text{ and } \alpha_t \) are firm, bank and month fixed effects respectively. The OLS estimation in column one includes only bank and month fixed effects. The firm FE estimation includes all three. The firm fixed effects require to reduce the sample to those borrowers that have debt with more than one bank (19,527 borrowers).

<table>
<thead>
<tr>
<th>Dependent Variable</th>
<th>OLS</th>
<th>Firm FE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Change in log Debt</td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>Change in Expected Cash Windfalls</td>
<td>0.0035**</td>
<td>0.0034**</td>
</tr>
<tr>
<td></td>
<td>[.0016]</td>
<td>[.0015]</td>
</tr>
<tr>
<td>Borrower FE</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>Bank/ Month FE</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
<td>371,512</td>
<td>371,512</td>
</tr>
</tbody>
</table>

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

Figure 1
Evidence on Loan Re-Labeling: Monthly Debt Evolution of the Firms that Received Program Loans, by Source

Source: own calculations using MYPES program database and CDSF credit bureau data. Based on a sample of 2,596 firms that received program loans after January 1996. The horizontal axis measures time in months relative to the moment of reception of the program loan (0 is the month the program loan was received by the firm).
Panel 1: Flow of Program Financing and Number of Participating Banks, by Year

Panel 2: Flow of Program Financing and Number of Participating Banks, by Wave

Source: own calculations using MYPES program data. The flow of financing during a year is the sum of the amount of resources allocated to all the waves that began during that year. The number of banks counts a bank only once even if it participated in two waves during a year.
Figure 3
Kernel Estimation of the Monthly Hazard Rate of Default

Source: Own calculations using Public Credit Bureau database from the sample of loans issued between January and August 1998. The vertical axis plots the weighted kernel density estimate utilizing the estimated monthly default hazard. The horizontal axis measures months elapsed after the loan was issued. Loan performance is observed until August 2001 where the sample is truncated to avoid the period of high default rates that preceded the December 2001 crisis in Argentina.
Liquidity constraints are understood broadly as frictions that increase the cost of external finance to the bank (Stein 1998). The terms liquidity constraints and financial constraints will be used interchangeably throughout the paper.

The optimal response of an unconstrained bank to a cash windfall that doesn’t affect the marginal cost of capital is to reduce market priced liabilities or to distribute it among investors as dividends. Expanding lending would yield a return below the opportunity cost of capital. The same underlying logic is behind the investment-cash flow literature in corporate finance and previous empirical work on the lending channel. See Stein (2003) for a recent survey on both.

These are estimates from a firm fixed effects specification which fully accounts for changes in the composition of bank lending during liquidity shocks. In other words, the estimates are derived from comparing the outcomes of a firm that receives a loan from a lender that in turn receives a cash windfall, with the same firm when it receives a loan from a bank that did not.

Poor budget execution is the main hurdle development agencies face when implementing on-lending programs (Barger 1998). Not surprisingly, the monitoring and auditing procedures are usually designed to minimize it, and the MYPES program was no exception. The government agency set up to monitor the implementation of the program focused on two criteria. First, that banks were actually issuing $1 of loans for every 75 cents of financing they received. And second, that program loans were given to firms that met the eligibility rules. The agency collected no information on whether the program loan recipients were borrowing from the bank before receiving a program loan or if they were, in what amount. I put together this information by merging the program database with the credit bureau database in the Central Bank.

There were four waves during this period to accommodate the contractual requirement that the entire program be implemented in 12 waves (only 8 waves had been used by January 1998). The size of the four waves is not strictly independent since the since the amount of financing in the four waves must add to the total resources left in the program budget by 1999. Nevertheless, the critical assumption to test for financing frictions is that the size and timing of the liquidity shocks is uncorrelated with changes in investment opportunities of the banks. If banks obtain finance in a frictionless market, their lending behavior should not be affected a completely predictable cash windfall.

Banks submitted in the application to the Central Bank the amount of financing required from the program. If the sum of the requested financing of all applicants exceeded the amount of resources in the wave (which it did in every wave), financing was distributed among applicants according to the formula in Section II.B. The formula assigns 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. The point score according to average loan size assigns a score of 100 for an average loan size between $0 and $3000, a score of 97 for average loan size of $3000 to $6000, and so on. Average loan sizes of $50,000 and above receive scores of 30 and below. The point score according to regional
distribution allocated a weight of 30 to loans issued in the richest provinces (Capital Federal, La Pampa y Santa Cruz) and 100 to loans issued in the poorest (Formosa, Catamarca, Santiago del Estero, Chaco, Jujuy, Misiones, Corrientes, Salta, Chubut y Tucumán). Loans to other provinces received a weight of 70.

7 For example, assume there are two banks A and B that are identical in all respects except that bank A suffers a shock to deposits that would lead to a decline in lending of $100. Now assume only bank A participates in the program and receives a cash windfall that exactly offsets the $100 decline. A researcher that compares banks A and B, would conclude that the cash windfall did not affect lending by bank A, while in fact it increased lending by $100. If banks self-selected into the program when they received negative liquidity shocks, the estimate of the sensitivity of lending to liquidity would be biased downwards. Similarly, an upward bias would result if banks self-selected when they received positive shocks in their returns to lending.

8 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.

9 Program administrators used the ratio of total bank loans to the number of loans as a proxy for average loan size. Since the objective here is to replicate the allocation rule used by program administrators, I use the same proxy even though the actual average loan size by bank can be obtained directly from the CDSF.

10 The variation in liquidity of banks that always participate or never participate is ‘partialed out’ in the first stage of the 2SLS.

11 The unconditional expected cash windfalls are given by \( \hat{p}_{in} \hat{C}_{iw} \). And, the expected cash windfalls by month, \( \hat{C}_{iu} \), are calculated assuming, 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.

12 The interest rate of each type of debt paid by bank \( i \) at month \( t \) is calculated dividing the interest rate accrued by type of debt at time \( t \) (from earnings report) by the stock of the same type of debt at \( t-1 \) (from balance sheet).

13 More traditional measures of investment opportunities, like Tobin’s q, are not available because small locally owned banks in Argentina are not publicly traded.

14 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 forgiveness, some collateral has being seized. Situation 5 (unrecoverable): bankruptcy declared. Situation 6
(unrecoverable by technical disposition): late repayments of more than 180 days with intervened financial institutions.

15 Since most of the variables considered in this paper are likely to have trends (loans, loanable funds), all variables will be first differenced in all specifications that follow. Note that a bank fixed-effects specifications with the variables in differences accounts not only for bank level time invariant characteristics, but also for differential bank specific trends in all variables.

16 I attempted to estimate the composition of the allocation of cash windfalls across different types of liquid assets, but the standard errors of estimates were too large to discern across them.

17 The size of the standard errors might raise concerns about the power of the test. Given the point estimate (-0.01) and standard error (0.02) of \( \psi_{24} \), a one tailed test would allow us to reject an increase in the probability of default of 1.6 percentage points at a 10% confidence level. Such an increase would be achieved if the default rate of the marginal loans of the bank were above 30%. This is not implausible since the average default rate is above 16%. Moreover, in the next section I show higher powered tests that indicate that cash windfalls reduced the probability of bankruptcy of loan recipients, which is consistent with the interpretation offered here.

18 This includes comparing the outcome of a borrower that received two loans from the same bank, one when the bank received a cash windfall and one when it did not. The firm fixed effects estimation requires reducing the sample to firms that receive more than one credit during the sample period (123,155 borrowers out of the original sample of 222,124). Also all loans to individuals are excluded from the sample.

19 Clustering at the bank level is no longer feasible since the data has been collapse at the borrower/month cell.

20 The firm fixed effects specification compares the change in the amount of debt of a firm that received the liquidity shock versus the amount of debt of that firm with other banks (requires reducing the sample to larger firms that borrow from more than one financial institution). I also include bank fixed effects to account for systematic differences across banks. This is possible in the empirical setting of this paper because identification does not rely on cross sectional comparison of banks.

21 In an unreported regression I find that this lending composition does not change during cash windfalls. This implies that the marginal bank loan is allocated across types of borrowers with the same composition than the average loan portfolio allocation.