Preliminary Draft

Measuring the Determinants of Average and Marginal Bank Interest Rate Spreads in Chile, 1994-2001

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Abstract

The study of bank interest rate spreads is central to our understanding of the process of financial intermediation. Data limitations generally restrict empirical analyses to interest rate spreads that are constructed from bank income statements and balance sheets. In this paper we make use of a data set that allows us directly to compute interest rate spreads based on individual bank loan and deposit rates reported on a monthly basis to the Central Bank of Chile. The information is disaggregated by unit of account (peso, inflation-indexed, and dollar) over the period 1994-2001. We find that the estimated impacts of industry concentration, business cycle variables, and monetary policy variables differ markedly between interest rate spreads based on balance sheet data and interest rate spreads based on disaggregated loan and deposit data. Since empirical work on interest spreads is used for guiding policy recommendations, these findings have important implications for the interpretation of interest spreads regressions. Our analysis calls for some caution in the interpretation of estimated empirical determinants of bank spreads that are constructed from income statements and balance sheet data. At the same time, our analysis shows how information from the two types of interest rate spreads can be combined to create a more complete portrait of bank behavior than either type alone is capable of creating. The results for Chile suggest the potential importance of gathering such disaggregated data in other countries.

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I. Introduction

Banking has long been recognized as an important factor in economic development. Adam Smith (1776) singled out Scottish banks as a reason for Scotland's growth.[1] Linkages between finance and development also played an important role in the work of Schumpeter (1911), Gurley and Shaw (1960), Goldsmith (1969), and McKinnon (1973). The link between finance and development has been affirmed more recently by Rajan and Zingales (1998). New work also stresses the importance of more efficient financial intermediation for economic growth as well as for the allocation of resources at any point in time.[2]

Whether or not the cost of financial intermediation plays a crucial role in financial development is a more disputed topic. On the one hand, many papers have focused on the negative impact of taxes (e.g., unremunerated reserve requirements) on the spread between loan and deposit rates.[3] This same literature emphasizes that financial repression raises the cost of finance in curb markets that spring up to circumvent excessive bank controls.

On the other hand, Goldsmith (1969, p. 47) believed that financial development in the United States, Canada, and Europe took place during the last two centuries with roughly stable costs of intermediation.[4] A theoretical justification for such a finding can be found in the credit rationing literature stemming from Stiglitz and Weiss (1981) where adverse selection in credit markets creates non-price rationing of credit. In addition, the use of collateral, escrow accounts, down payments, and other contractual provisions can affect the expected loan return without explicitly altering the contractual interest rate.

Despite these *caveats* concerning the role of non-price factors in financial intermediation, policymakers generally pay attention to bank interest rate spreads. Mergers and acquisitions of banks sometimes produce increased interest rate spreads that raise anti-trust issues. Central banks worry about increases in spreads during times of financial distress. And capital account liberalization is often accompanied by changes in interest rate spreads that raise concerns about financial stability.

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[1] One relevant passage refers to the expansion of commercial credit: "The commerce of Scotland, which at present is not very great, was still more inconsiderable when the two first banking companies were established; and those companies would have had but little trade, had they confined their business to the discounting of bills of exchange. They invented, therefore, another method of issuing their promissory notes; by granting what they call cash accounts. Credits of this kind are, I believe, commonly granted by banks and bankers in all different parts of the world. But the easy terms upon which the Scotch banking companies accept of repayment are, so far as I know, peculiar to them, and have perhaps been the principal cause, both of the great trade of those companies, and of the benefit which the country has received from it." (Book II, Section 2: Of Money Considered as a particular Branch of the General Stock of the Society)

[2] See, for example, King and Levine (1993), Greenwood and Smith (1997), and Cetorelli and Gambera (2001).

[3] See the papers in Honohan (2003) for recent treatments of this topic.

[4] Goldsmith (1969, p. 91) states that "Interest rates are thus secondary, though by no means unimportant determinants of the [financial interrelations ratio, FIR]….They are in much the same position as…the asset preferences of different groups of holders and issuers of financial instruments, the legal provisions affecting the issuance of securities and the operation of financial intermediaries, the policy of the monetary authorities, and the factors determining the balance of payments."

In an influential paper Bernanke (1983) defined the cost of financial intermediation (*CFI*) to be the wedge between the gross cost paid by a borrower to a bank and the net return received by a saver.[5] In practice, most empirical work approximates the *CFI* in the banking industry through balance sheet and income statement data. The idea is to obtain "implicit" loan and deposit rates offered by each individual bank. The question then is which is the best method to obtain such an "implicit rate". Although there is no single definition for interest margins in the empirical literature[6], the predominant one is the net interest margin (*NIM*), the ratio of total interest revenue minus total interest expenses as percentage of earning assets. By including expenditures and income from all types of deposit and loan operations, the net interest margin creates an average interest spread. Empirical work, primarily reduced-form regressions analysis, has examined the impact of (aggregate and idiosyncratic) risk[7], industry structure[8], macroeconomics[9] and regulatory issues[10] on *NIM*s. Recent studies have provided benchmark analyses of *NIM*s for the Chilean financial system.[11]

Due to lack of data, there are almost no studies that use actual loan and deposit interest rate data by individual banks.[12] In most cases, banks do not report the whole array of specific interest rates charged and paid.[13] Recent papers study interest rate spreads using disaggregated data by type of operation but not by individual banks. For example, Catao (1998) uses Argentinean aggregate Pesos and US dollar deposit and lending rates to study the determination of spreads under a dual currency framework. Agénor, Aizenman and Hoffmaister (1999) use the same dataset to study the impact of contagion and output fluctuations on spreads. Finally, Corvoisier and Gropp (2001) study the effects of concentration in EU banking systems using different types of loans and deposit rates. Two other papers use individual bank data from Italy that was collected after the introduction of a usury law in 1997.[14]

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[5] Bernanke argued the *CFI* plays a fundamental role in the efficient allocation of credit. According to his view, the disruption of the financial sector by the banking and debt crises in the Great Depression raised the real cost of intermediation between lenders and borrowers, which reinforced the decline in aggregate output.

[6] See, for example, Brock and Rojas-Suarez (2000). In that paper, six different measures of interest margins are used in order to deal with measurement problems that arise when using accounting data to approximate the CFI.

[7] The studies about the relationship of bank margins with default and/or interest rate risk include Ho and Saunders (1981), Angbazo (1997), McShane and Sharpe (1985), Brock and Rojas-Suarez (2000), and Saunders and Schumacher (2000).

[8] Among the studies of bank concentration and *NIM*'s are McShane and Sharpe (1985), Ruthenberg and Elias (1996), Williams (1998), Barajas, Steiner, and Salazar (1999), Saunders and Schumacher (2000), Sinkey and Carter (2000), and Claessens, Demirguc-Kunt, and Huizinga (2001).

[9] The relation between business cycle variables and net interest margins is examined in Demirguc-Kunt and Huizinga (1999) and Brock and Rojas-Suarez (2000).

[10] Angbazo (1997) examines the effects of capital requirements.

[11] The *NIM* studies include Fuentes and Basch (2000) and Ahumada and Budnevich (1999). In the broader context of this study, Berstein and Fuentes (2003) analyze the pass-through of changes in the monetary policy rate to loan rates, while Budnevich, Franken, and Paredes (2001) look at economies of scale and scope in the Chilean banking industry.

[12] Interest rate net income accounts for 80% or more of bank profits as reported in Mercer (1992).

[13] Banks do not always publish even the prime rate or, on the liability side, retail deposit rates.

[14] These are Alessie, Hochguertel, and Weber (2001) who analyze the impact of the introduction of this usury law and Bertola, Hochguertel and Koeniger (2002) who study the effects of price discrimination in the spread between borrowing and lending rates.

Our paper makes use of a dataset for Chile that contains interest rate data by individual banks and by type of operation. We also make use of balance sheet and income statement data to calculate interest margins for each bank. Our study is the first one to use both individual bank data as well as balance sheet data for the calculation of interest rate spreads in order to study issues that affect the cost of financial intermediation. We find that measures of volatility (risk) affect margins based on bank balance sheet data and spreads based on interest rate data in the same way. However, the estimated impact of concentration and macro variables (business cycle and monetary policy) differs markedly depending on whether balance sheet data or disaggregated interest rate data is used to construct the spreads.

The rest of the paper is organized as follows. Section II develops the analytical motivation for empirical estimates of the determinants of interest rates spreads. Section III describes the data and the empirical specification. The results are contained in section IV and section V concludes.

II. Models of Interest Rate Spreads

FINANCIAL MARKET MICROSTRUCTURE

Almost all empirical models of bank spreads cite the influential dealership model of Ho and Saunders (1981), in which banks are modeled as if they operate like dealers setting bid-ask spreads in securities markets. Although the research on bid-ask spreads in securities markets is not the primary focus of this paper, it forms a useful point of departure for the examination of models of banking spreads. Beginning with the work of Demsetz (1968) researchers in empirical finance have sought to measure the determinants of bid-ask spreads in securities (primarily stock) markets.[15] Demsetz provided the theoretical argument for the existence of dealers in securities markets: dealers provide immediacy (liquidity) that allows other market participant to buy and sell securities instantaneously. In order to provide immediacy, dealers must hold an inventory of stocks and to be compensated for the costs of operation by charging a spread between the selling and buying price. Over time, and especially with the work of Stoll (1978), these costs have become categorized into three types.[16] The first type is *order-processing costs*. These are the costs associated with operating as a dealer, including the rental of floor space, the cost of a seat on the exchange, computer costs, and so on. The second type is *inventory-holding costs*. These are the opportunity cost of the dealer's funds plus the costs associated with uncertainty regarding the movement of the stock price. For risk-averse dealers, the uncertainty in stock price movements creates a cost associated with the risk of buying high and being forced to sell low. The third type is *adverse selection costs*. These costs arise from the fact that there are informed market participants who have inside information about future stock price movements. To protect himself/herself against these participants, the dealer is forced to widen the spread. Finally, the market

[15] The bid-ask spread is the difference between the price at which a dealer will sell a security and the price at which the dealer will buy the security.
[16] See Bollen, Smith, and Whaley (2003) or Stoll (2003) for a more detailed discussion of these costs.

microstructure literature has also recognized that *market concentration* may also affect the size of the bid-ask spread.

These four factors--order-processing costs, inventory-holding costs, adverse selection costs, and market structure--form the basis for empirical work on bid-ask yields. Various proxies have been used for these factors in linear regression models. A common proxy for order-processing costs is trading volume (with an expected negative sign). There have been many proxies for inventory holding costs, of which share price (expected positive sign) and standard deviation of price or return (expected positive sign) are typical. Adverse selection costs have been captured by the ratio of dollar trading volume to market capitalization (expected positive sign) as well as other similar measures. Market concentration is often measured by the Herfindahl index or the logarithm of the number of dealers (expected positive sign).

The growing sophistication of empirical work in this area has been aided by the development of mathematical models of the dealer's optimization problem. Among these, Stoll (1989) and Bollen, Smith, and Whaley (2003) are noteworthy for developing models of the interaction of adverse selection (traders with inside information) and stock price uncertainty with the setting of the bid-ask spread.

BANK INTEREST RATE SPREADS

The market microstructure literature has identified the purpose of the dealer as one of providing liquidity to participants in the market. Unlike the dealer, banks have several purposes. Banks provide a means of payment (demand deposits), issue and hold non-liquid loans, engage in asset transformation (e.g., duration transformation from long-term loans to short-term deposits, unit of account transformation from dollar liabilities to local currency denominated assets), and provide off-balance-sheet services (interest rate swaps, letters of credit, etc.). Banks typically also operate with deposit insurance and are often required to hold non-interest bearing required reserves. It is commonly argued that the structure of the bank balance sheet arises as a result of information asymmetries between borrowers, bankers, and depositors.

The bank's several purposes are more complex than the dealer's problem of providing immediacy. Not surprisingly, there is no commonly agreed counterpart in banking to the bid-ask spread in securities markets. Indeed, in this paper we discuss the relative merits of net interest margins, average spreads, and marginal spreads as they relate to a bank's operations. We identify the conceptual difference between empirical regressions of spreads that are based on bank accounting identities and those which are motivated by maximizing models of bank behavior. We suggest that different margins and spreads provide complementary empirical points of departure that can help to explain the behavior of banks in response to changes in market structure, interest rate uncertainty, and macro variables.

Consider the following stylized bank balance sheet:

Assets	Liabilities
Required Reserves (*R*)	Demand Deposits (*DD*)
Short-term Assets (A_S)	Time Deposits (*D*) (Short-term)
Long-term Assets (A_L)	
	Equity (*E*)

The following three types of spreads come out of this balance sheet:

$$Net\ Interest\ Margin,\ \ NIM \equiv \frac{r_A A - r_D D}{A},$$

$$where\ \ A = A_S + A_D\ \ and\ \ r_A = \frac{r_S A_S + r_L A_L}{A}$$

$$Average\ \ Spread \equiv r_A - r_D$$

$$Marginal\ \ (interest\ \ rate)\ \ spreads$$

$$r_S - r_D \qquad (matched\ \ maturity)$$

$$r_L - r_D \qquad (long)$$

The *NIM* measures an average return on assets relative to the explicit interest cost of funding those assets: the average return on assets is r_A while the *average* cost of funding those assets is $r_D D / A$. The *average spread* is the difference between the average return on assets, r_A, and the *marginal* cost of funding out of time deposits, r_D. The *NIM*, with its implicit inclusion of demand deposits and equity as zero-cost sources of funds, is useful in demonstrating profitability that permits banks to cover their fixed costs of operation. The average spread, with its emphasis on the marginal cost of funding new assets, is a good measure of the marginal cost of financial intermediation between borrowers from banks and marginal providers of funds. Both measures are of interest to policymakers interested in the viability of banks (ability to cover fixed costs) and the marginal efficiency of intermediation.

Marginal spreads reflect the bank's willingness to take *duration risk* (borrow short, lend long) with some fraction of the bank's assets, while matching asset and deposit maturities (borrow short, lend short) with the other fraction of the assets. Marginal spreads also arise when banks take *unit of account risk* by issuing domestic currency and dollar deposits that don't match domestic currency and dollar loan positions. The marginal spreads contain information that is not accessible by using the average spread or the NIM. As a result, the marginal spreads can give an additional perspective on the process and cost of intermediation.

As an empirical matter (discussed more fully in Section III), we measure the *NIM* and the Average Spread using balance sheet and income statement figures, while marginal spreads use actual loan rate and deposit rate data that banks report to the Superintendent of Banks.

EMPIRICAL ESTIMATION OF INTEREST MARGINS AND SPREADS

The most common way to estimate the determinants of net interest margins is to start with the bank income statement:

$$r_A A \equiv r_D D + NoninterestExpenses + Costs + Provisions + r_E Equity \qquad (1)$$

where *NoninterestExpenses* refers to the expenses spent on servicing demand accounts minus commissions banks receive for off-balance sheet activities, *Costs* refers to overhead costs, *Provisions* are against loan write-offs, and $r_E Equity$ is *Profits* (return on equity times bank equity capital). Beginning with the income identity, an expression for the *NIM* is easily derived:

$$NIM \equiv \frac{r_A A - r_D D}{A} \equiv \frac{NoninterestExpenses}{A} + \frac{Costs}{A} + \frac{Provisions}{A} + r_E \frac{Equity}{A} \qquad (2)$$

Regressions based explicitly on this identity are very common.[17] Many other studies use this identity as the core of regressions that include other variables as well.[18]

COST FUNCTION APPROACH TO ESTIMATION OF THE SPREAD

The income accounting identity can also be used to derive an expression for the spread based on maximizing behavior on the part of banks. There are several relevant models. The first, which is known as the Monti-Klein bank model,[19] is based on the assumption that there is a cost function for running a bank that depends on the aggregate value of the assets being managed by the bank as well as other factors of production, such as capital and labor (*K*,*L*): $Costs = C(A; K, L)$. Assuming that a bank maximizes profits, the income accounting identity becomes:

$$Profits = r_A A - r_D D - C(A; K, L) - Provisions \text{ - } NoninterestExpenses \qquad (3)$$

Profit maximization for a competitive bank leads to the following first-order conditions (where $dD = dA$ on the margin):

$$r_A - r_D = \frac{\partial C(A; K, L)}{\partial A} \qquad (4)$$

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[17] See, e.g. Demirguc-Kunt and Huizinga 1999, and Claessens, et.al. 2001.

[18] See Ho and Saunders (1981), Sinkey and Carter (2000), Angbazo (1997), Demirguc-Kunt, Laven, and Levine (2003).

[19] This model was originally developed by Klein (1971) and Monti (1972).

The first-order conditions state that a competitive bank will set the marginal cost of managing assets equal to the spread. All the other components of the accounting identity drop out because they involve inframarginal profits. If marginal costs are linear in assets, then the spread equation becomes:

$$r_A - r_D = \beta_1 A + \beta_2 K + \beta_3 L \tag{5}$$

If instead of a competitive banking system in which banks take interest rates as exogenously given, the banking system is assumed to be a monopoly, then profit maximization leads to the following condition:

$$\begin{aligned} r_A - r_D &= D\frac{\partial r_D}{\partial D} - A\frac{\partial r_A}{\partial A} + \frac{\partial C(A;K,L)}{\partial A} \\ &= \frac{1}{\eta_D} + \frac{1}{\eta_A} + \frac{\partial C(A;K,L)}{\partial A} \end{aligned} \tag{6}$$

where η_A, η_D are semi-elasticities of asset supply and deposit demand ($\eta_A = -\frac{1}{A}\frac{dA}{dr_A}$, $\eta_D = \frac{1}{D}\frac{dD}{dr_D}$). In a banking system characterized by an oligopoly, the spread will be a function of the number of banks in the system. In particular, under the assumption of a common linear cost function and Cournot behavior, the spread will be given by the following expression:

$$r_A - r_D = \frac{1}{N}(\frac{1}{\eta_A} + \frac{1}{\eta_D}) + \beta_1 A + \beta_2 K + \beta_3 L \tag{7}$$

where N is the number of banks.[20] Equation (7) suggests that changes in the concentration of a banking system will affect the spread by altering the size of oligopoly profits. Equation (7) emphasizes that increases in the spread are apt to be associated with a decline in the number of banks and with an increase in marginal costs of processing deposits and assets. A commonly used empirical proxy for concentration in banking is the Herfindahl Index calculated in terms of total assets. If the Herfindahl index is used as a proxy for concentration, then equation (8) becomes:

$$r_A - r_D = \beta_1 A + \beta_2 K + \beta_3 L + \beta_4 Herf \tag{8}$$

Empirical estimates of the spread that are based on this cost function approach include Spiller and Favaro (1984), Barajas, Steiner, and Salazar (1999, 2000), Ruthenberg and Elias (1996), and Corvoisier and Gropp (2001). In our regressions in this paper we

[20] See Freixas and Rochet (1997).

assume that marginal costs of making loans are linear in loans, the number of bank branches (a form of capital), and the ratio of loans to employee:[21]

$$r_A - r_D = \beta_1 Loans + \beta_2 Branches + \beta_3 Loans / Emp + \beta_4 Herf \tag{9}$$

INCORPORATING UNCERTAINTY

The basic results of equations (8) and (9) rely on a production function approach that could be applied to any industry. What is special about banks is that they bear financial risk as an integral part of being financial intermediaries. There are two fundamental risks to consider: credit risk and liquidity risk.

Credit risk concerns the probability that a borrower will default on a loan. In order to manage credit risk, banks frequently require collateral to back up the loan, incorporate restrictive covenants into the use of the loan, and monitor the use of the loan. This suggests two ways in which a riskier loan portfolio will translate into a higher spread. First, the more intensive use of the bank's productive resources to service risky loans will raise the spread. Second, the higher probability of default will result in a risk premium on the loan rate even in the presence of restrictive covenants and monitoring.

Empirical studies of bank spreads generally use loan write offs, the delinquent loan portfolio, or provisions as indicators of default risk. The problem with these measures is that they are often backward-looking (reflecting realized defaults) rather than forward-looking proxies for default risk. In our own empirical work, we use the Superintendence of Banks' risk index, which attempts to be a forward-looking measure of credit risk.

A second type of risk is liquidity risk. Liquidity risk is similar to dealer risk in securities markets. A dealer providing liquidity to the market faces the risk that subsequent to buying a security its price could fall, creating a loss for the dealer. Similarly, a bank faces potential losses from interest rate movements.

In the dealership model originally advanced by Ho and Saunders (1981) the role of a bank is to provide liquidity to the market. The provision of liquidity by its own nature implies holding a position (either long if it grants too many loans or short if it takes too many deposits). In this model, banks are not able to match up deposits with loans since they are confronted with stochastic arrivals of depositors and borrowers. Thus, the bank has to consider the risk of an unbalanced portfolio $I = L - D$, i.e. the bank's net inventory that results from its commercial activity. In this framework it can be shown that the optimal spread between the loan rate and deposit rate is

$$spread \equiv r_L - r_D = \frac{\alpha}{\beta} + \frac{1}{2}\rho\frac{\sigma_I^2 Q}{(1+r)} \text{ .[22]} \tag{10}$$

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[21] This would correspond to a cost function of the form $\text{C(A,K,L)=}(\beta_1/2)\text{A}^2 + \ln A(\beta_2 K + \beta_3 L)$.

[22] See Ho and Saunders (1981) or Freixas and Rochet (1997) for the derivation.

The term α / β is the risk neutral spread[23] that would be chosen by a risk-neutral banker[24]. The other term is a risk premium, proportional to the risk aversion coefficient ρ, and increasing in the variance of return (σ_I^2) on the credit market activities that the bank engages in and the size of the transaction (*Q*). Finally, the spread is decreasing in the level of the monetary policy rate (*r*).

There are several extensions to the dealership model in the literature. For example Allen (1988) includes cross-elasticities of demand between banks products, which induces a more active role in managing its inventory risk exposure, and Angbazo (1997) includes loan default risk. It would be straightforward to extend the dealership model to international activities as well as transactions both in non-indexed and indexed instruments in an inflationary economy. Such extensions would bring out exchange rate and inflationary uncertainty risk premiums.

The results of the dealership model can be incorporated with those of the cost-structure approach to motivate a linear regression framework that incorporates credit risk and liquidity risk:

$$r_A - r_D = \beta_1 Loans + \beta_2 Branches + \beta_3 \, Loans/Emp + \beta_4 Herf + \beta_5 Default + \beta_6 \sigma_r^2 + \beta_7 \sigma_e^2 \quad (11)$$

where the two major types of liquidity risk in an open economy are interest rate risk (σ_r^2) and exchange rate risk (σ_e^2).[25]

OTHER CONSIDERATIONS FOR DETERMINING THE SPREAD

According to a recent Moody's report, "macroeconomic factors are certainly among the most influential sources for variations in credit spreads." Nevertheless, there is no generally agreed upon model for analyzing the consequences of macroeconomic shocks for interest rate spreads. In some models a positive shock to income lowers spreads by improving the net worth of borrowers.[26] In others, a collateral squeeze[27] has an ambiguous effect on interest rate spreads, while either a savings squeeze or a credit boom decreases spreads unambiguously.[28] The latter results compare to the ambiguous effects of a positive expenditure shock (which will be probably translated in a credit boom) in a

[23] The size of α and β determine the elasticity of the demand for loans and supply of deposits. Consequently the ratio α / β provides some measure the degree of monopoly power.

[24] Traditional explanations for risk aversion behavior in banks include: management's inability to diversify its human capital, insufficient owner diversification, incentive problems such as moral hazard and adverse selection and bankruptcy cost. In practical grounds, the dealership framework needs this assumption for the spread to exist, as well as, to ensure a finite bank size.

[25] Ho and Saunders used the net interest margin as the empirical proxy for the interest rate spread. They used several terms (reserves/assets, net fee expense/assets, and net loan chargeoffs/assets) from the *NIM* accounting identity as proxies for the risk-neutral spread.

[26] See, for example, Bernanke and Gertler (1989, 1990), whom identify the CFI with the collateralizable net worth of firms, because higher collateral values lower the agency costs associated with the enforcement of loan contracts.

[27] That is to say, a negative shock to assets.

[28] See, for example, Holmstrom and Tirole (1997).

different model.[29] Finally, there is a model that predicts that a negative productivity shock (that could cause a saving squeeze) will be positively related to bank lending spreads.[30] In addition, loan rate stickiness[31] or deposit rate rigidities[32] will add more complexity to the effects of macroeconomic shocks to spreads, making it difficult to predict the overall change.

Because of the theoretical ambiguity regarding the impact of macroeconomic shocks on the spread, we include only a few variables that we think have an easily discernable connection to the spread. The first is the slope of the yield curve, which is the difference in yields between 8 year and 90 day inflation-indexed instruments issued by the Central Bank. Because banks are engaged in maturity transformation, we expect that the net interest margin and the spread based on balance sheet data will covary positively with the spread. On the other hand, disaggregated spreads based on matched-maturity operations in pesos, UFs, and dollars may not show any effect of variations in the term structure of interest rates. The second is a measure of the gap between actual and trend GDP. This variable allows us to determine whether empirically there is a relationship between the business cycle and interest rate spreads.

We also include an index of capital controls, a dummy variable for the onset of the Asian crisis, and an additional dummy related to a regulatory change that required the incorporation of commissions in the calculation of the loan rate. Based on the *NIM* accounting identity approach to spreads (equation 2), we also include the capital/asset ratio and noninterest expenses as explanatory variables, even though those variables would not be included based on the profit-maximizing approach of the Monti-Klein model. In the end, we estimate a regression equation that combines microstructure variables with additional macro and regulatory determinants of spreads:[33]

$$\begin{aligned} r_A - r_D = {} & \beta_0 + \beta_1 NoninterestExp + \beta_2\, Cap/Asset + \beta_3 Default + \beta_4 Loans/Emp \\ & + \beta_5 Loans + \beta_6 Branches + \beta_7 Herf + \beta_8 \sigma_r^2 + \beta_9 \sigma_e^2 + \beta_{10} Yieldcurve \\ & + \beta_{11} OutputGap + \beta_{12} CapControls + \beta_{13} AsiaCrisis + \beta_{14} Commissions. \end{aligned} \tag{12}$$

[29] In the modified IS-LM framework of Bernanke and Blinder (1988), for example, the spread will unambiguously decrease with a expenditure shock if and only if the demand for loans is sufficiently elastic with respect to the loan rate.
[30] This happens in the model of Agenor, Aizenman and Hoffmaister (1999).
[31] Caused for example by smoothing relationship lending as in Petersen and Rajan (1994).
[32] Caused for example by differences in local market concentration as in Neumark and Sharpe (1992).
[33] See Section III for a more precise econometric presentation of the estimating equations, including lag structure, fixed effects, and seasonal dummies.

III. Data Description and Empirical Specification

As emphasized in Section II, the most common measure in the empirical literature for a bank spread is the *net interest margin*. A second measure, the *Average Spread*, divides total interest income by total earning assets, and total interest expenses by total cost accruing liabilities. The data needed to construct both measures is taken from the balance sheet and income statements of individual banks. In the case of Chile, the Superintendency of Banks and Financial Institutions (SBIF) publishes such information on a monthly basis.[34]

Our second source of data is the Central Bank of Chile (BCCH). In particular, we use a dataset constructed at the BCCH[35], which contains loan and deposit interest rates, by bank, disaggregated by term and unit of account. This dataset is available beginning in May 1994. For the purposes of this study, we include data from July 1994 to July 2001. The dataset includes all banks operating in the Chilean banking industry during the sample period[36]. Table III.1 summarizes the level of disaggregation available:

Table III.1: Interest Rate Data Availability

By Term	By Unit of Account
Less than 30 days	Chilean Peso (Peso)
30 to 89 days	Unidad de Fomento (UF)
90 days to 1 year	US dollar (Dollar)
1 year to 3 years	
more than 3 years	

The use of three units of account in Chilean financial markets began in the 1970s as a response to high and ongoing inflation from 1973 through the end of the 1970s. Short-term peso deposits and loans bearing high nominal interest rates were initially the dominant financial instruments following the liberalization of financial markets in 1974. That same year the Chilean government introduced an inflation indexation mechanism called the Unidad de Fomento (UF). The UF for any given month is based on the previous month's consumer price index.[37,38]

[34] Monthly Statistical Bulletin (Información Financiera). We are thankful to the Capital Markets Department (Financial Policy Division - Central Bank of Chile) for providing us this data set in an electronic form.

[35] Macroeconomic Analysis Unit, Research Division.

[36] Banks with few observations and banks with many outliers in terms of spreads and net interest margin data where dropped from the sample. We are then left with 27 banks ($i = 1,...,N$ and $N = 27$). Since this is a monthly data set, we have 85 time series observations ($t = 1,...,T$ and $T = 85$). The data set is unbalanced.

[37] Daily increments in the value of the UF are calculated by taking (typically) one thirtieth of the rise in the CPI in the preceding month. Since the calculation of the CPI takes about a week, the coverage of the UF begins on the tenth calendar day of the month and goes through the ninth day of the succeeding month

[38] The first indexed deposit contracts in UF were introduced in 1976. The UF has proven to be a durable feature of the Chilean economy. Inflation-indexed deposits have allowed the Chilean financial markets to operate as if inflation were zero. See the Appendix to Fontaine (1995) for a discussion of the history and properties of the UF.

Table III.2 summarizes the total shares of loans and deposits by term and unit of account:

Table III.2: Loan and Deposit Shares								
	Peso		UF		Dollar		Total by Term	
	Loan	Deposit	Loan	Deposit	Loan	Deposit	Loan	Deposit
Less than 30 days	35.5	-	4.7	-	1.2	-	41.4	-
30 to 89 days	14.2	54.0	8.4	0.9	2.5	10.1	25.1	65.0
90 days to 1 year	9.4	0.2	13.8	29.4	5.2	1.2	28.4	30.8
More than 1 year	2.0	0.7	2.8	3.5	0.3	0.0	5.1	4.2
Total by Unit of Account	61.1	54.9	29.7	33.8	9.2	11.3	100	100

One of the important features of banks is that they engage in asset transformation. Such asset transformation activities usually involve both term structure and unit of account transformation. Accounting data tends to average out this important feature of banks' operations. In order to demonstrate this point, we construct several measures of spread using interest rate data for different terms and units of accounts. The first one, which we call the *long spread*, is defined as the difference between loan rates in pesos for more than 1 year and deposit rates in pesos from 30 to 89 days. The other three spreads use loan and deposit interest rates at similar maturities. For the *peso spread* and *UF spread* we choose the most important maturities, which are 30 to 89 days and 90 days to 1 year, respectively[39]. Finally, given the relative thinness of the market for loans and deposits in dollars, which amounts on average to only 10% of total loans and deposits, we construct a more mixed measure for the *dollar spread*. The latter includes all loans and deposits in dollars with maturity greater than 30 days and shorter that 1 year, which covers almost ninety percent of loans and almost one hundred percent of deposits in that currency.

In summary, our dependent variables for banking spreads both from accounting and interest rate data are the following:

1. $$\text{Net Margin} = \frac{\text{Total Interest Income} - \text{Total Interest Expenses}}{\text{Total Earning Assets}}$$

2. $$\text{Average Spread} = \left(\frac{\text{Total Interest Income}}{\text{Total Earning Assets}}\right) - \left(\frac{\text{Total Interest Expenses}}{\text{Total Accruing Liabilities}}\right)$$

3. $$\text{Long Spread} = i^{\text{More than 1 year}}_{\text{Loans in Pesos}} - i^{\text{30-89 days}}_{\text{Deposists in Pesos}}$$

[39] Notice that for the case of peso loans the largest share by term corresponds to less than 30 days. However, there is no deposit interest rate counterpart to construct a spread for such a term, since law prohibits time deposits for less than 30 days. Therefore, we use 30 to 89 days, the second largest loan share in pesos.

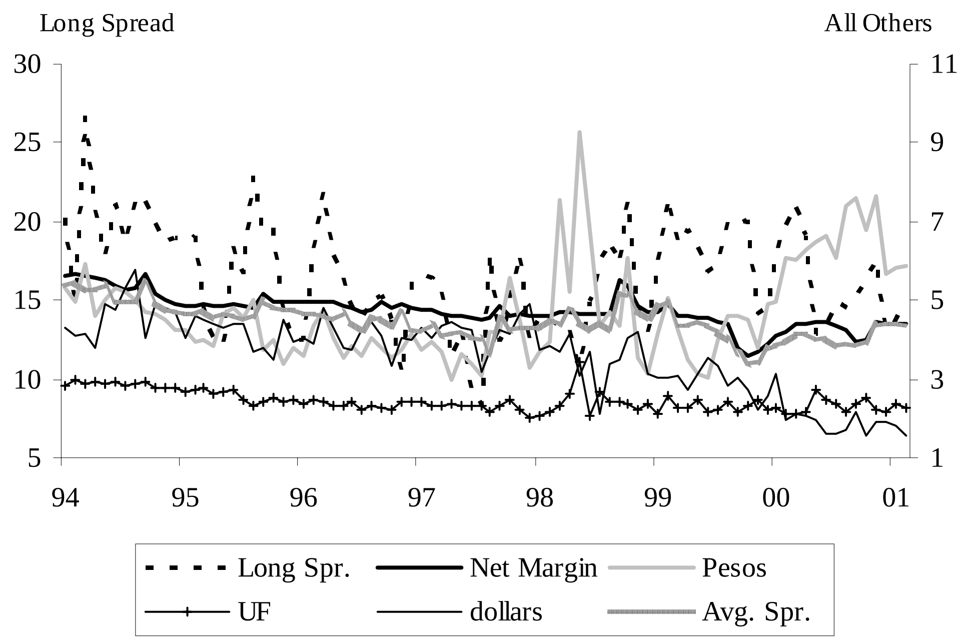
4. $\text{Peso Spread} = i^{\text{30-89 days}}_{\text{Loans in Pesos}} - i^{\text{30-89 days}}_{\text{Deposists in Pesos}}$

5. $\text{UF Spread} = i^{\text{90 days-1 year}}_{\text{Loans in UF}} - i^{\text{90 days-1 year}}_{\text{Deposists in UF}}$

6. $\text{Dollars Spread} = i^{\text{30 days-1 year}}_{\text{Loans in Dollars}} - i^{\text{30 days-1 year}}_{\text{Deposists in Dollars}}$

Figure III.1 shows the evolution of our measures of spreads within the sample period. The NIM and the Average Spread, which are constructed from balance sheet data, are much smoother than the long spread, the peso spread, and the dollar spread. The UF spread is also relatively smooth, primarily because the Central Bank's monetary policy targeted the price-level indexed interest rate. The large movements in the interest rate spreads in late 1997 and 1998 reflect the domestic response to the Asian and Russian crises.

Figure III.1: Measures of Spreads
(Banking System; percentage)



For the purpose of organizing the discussion of the results in section IV, the explanatory variables will be classified within five categories. The first one corresponds to bank characteristics. These include implicit interest payments, capital adequacy, asset quality, and management efficiency. All of these variables are constructed from the data published by the SBIF. Whereas the first category accounts for idiosyncratic characteristics/risks, the second group of variables controls for aggregate risks that are related to spreads through the risk premium. The third group of variables is related to industry structure, and the fourth group to some relevant policy issues associated with spreads, typically included in both the theoretical and empirical literature of banking spreads. These are the relation of spreads to the business cycle, monetary policy and capital account controls. Finally, we include two dummy variables aimed to account for some important events that occurred over the sample period. Table III.3 contains the specific description of the explanatory variables.

	Table III.3: Variables Description	
Variable	**Specific Description**	
Implicit Payments	Implicit Interest Payments[40]	**BANK CHARACTERISTICS**
Capital/Assets	Capital Ratio (Adjusted Equity[41] over Adjusted Assets[42])	
Asset Quality	Risk Index of the Loan's Portfolio[43]	
Loans/Employees	Total Loans over Number of Employees	
Interest Rate Volatility	Interest Rate Risk[44]	**AGGREGATE RISKS**
Exchange Rate Volatility	Nominal Exchange Rate Risk[45]	
Size	Total Assets of $Bank_i$ over Total Assets of the Banking System	**INDUSTRY STRUCTURE**
Branches	Number of Branches	
Concentration	Herfindahl Index in Terms of Total Loans	
Slope of the Yield Curve	Slope of the Yield Curve[46]	**POLICY ISSUES**
Output Gap	Deviation of Log(IMACEC[47]) from its Trend (HP filter)	
Capital Controls	Index of Capital Account Controls	
Asian Crisis	Dummy that Takes Value of 1 After the Asian Crisis[48]	**DUMMY VARIABLES**
Regulatory Change	Dummy that Takes Value of 1 After a Regulatory Change Related to Loans Commissions [49]	

An important question before engaging in a Panel Data estimation is whether or not such an analysis incorporates valuable information. A common way to answer this question is to look at the dispersion of data among banks and over time. Table III.4 shows the coefficient variations (the ratio between the standard deviation and the mean) for the variables that span both cross-sections and time. For most of the variables considered in our analysis the dispersion among banks is much larger than the dispersion over time. This finding has also being reported in other countries. As stated by Brock and Rojas-

[40] Overhead costs + commissions expenses – commissions income. This variable is aimed to account for service charge remissions.
[41] Equity + voluntary provisions + subordinated bonds – investments in related enterprises - investments in branches abroad.
[42] Total assets – forward liabilities – other accounting adjustments.
[43] This index is calculated by the SBIF. A higher index number implies a lower quality of assets.
[44] Measured as the monthly average daily standard deviation of the interbank interest rate.
[45] Measured as the monthly average daily standard deviation of the nominal exchange rate.
[46] Measured by the difference between PRC8 and PRBC90. These are 8-years and 90-days maturity UF instruments issued by the BCCH, respectively.
[47] IMACEC is the Monthly Index of Economic Activity.
[48] Second half of 1997.
[49] The interest rate of any loan must include now any type of commissions. Such regulations are part of the new guidelines to calculate maximum loan rates. They took place in mid-1999 for loans with maturity larger than 90 days and the first quarter of 2000 for loans with a shorter maturity.

Suarez (2000), such striking differences imply that "*it may be misleading to focus on aggregates to understand the behavior of spreads*".

Table III.4: Coefficient Variations		
Variable	**Over Time**	**Among Banks**
Net Margin	0.21	1.18
Long Spread	0.20	1.15
Peso Spread	0.23	0.39
UF Spread	0.12	0.21
Dollar Spread	0.21	0.19
Implicit Payments	0.16	0.86
Capital/Assets	0.10	0.85
Asset Quality	0.28	0.30
Loans/Employees	0.16	0.59
Size	0.10	1.15
Branches	0.12	1.14

Finally, descriptive statistics of the dependent and explanatory variables included in our regressions are shown in table III.5.

Table III.5: Descriptive Statistics of Variables Included in the Regressions						
Variable	**N° of Banks**	**N° of Obs.**	**Mean**	**Std. Dev.**	**Minimum**	**Maximum**
Net Margin	27	2199	6,7	7,8	0,0	43,4
Average Spread	27	2199	6,1	8,0	0,0	43,7
Long Spread	27	2206	15,1	6,7	0,0	43,0
Peso Spread	27	2206	0,4	0,3	0,0	2,3
UF Spread	27	2206	2,6	0,9	0,3	9,7
Dollar Spread	27	2242	4,3	1,4	0,0	10,3
Implicit Payments	27	2199	2,6	1,7	0,4	12,2
Capital/Assets	27	2196	14,3	12,7	4,7	82,0
Asset Quality	27	2203	1,6	1,0	0,1	8,9
Loans/Employees	27	2203	41,5	25,5	3,4	151,8
Interest Rate Volatility		85	2,1	2,3	0,2	12,7
Exchange Rate Volatility		85	48,6	44,8	4,8	318,6
Size	27	2203	3,5	3,9	0,0	16,6
Branches	27	2203	57,2	65,8	1,0	302,0
Concentration		85	8,5	0,8	7,0	9,3
Slope of the Yield Curve		85	-0,2	1,3	-8,7	1,5
Output Gap		85	0,0	0,0	0,0	0,0
Capital Controls		85	30,5	21,7	0,0	60,5
Asian Crisis		85	0,6	0,5	0,0	1,0
Regulatory Change		85	0,3	0,5	0,0	1,0

The empirical specification outlined above (in words) can be summarized as follows:

$$y_{it} = c + \alpha_i + \gamma_1 y_{i,t-1} + \beta' x_{i,t-2} + \phi' z_t + \delta_A d_{\text{Asian Crisis}} + \delta_R d_{\text{Reg. Change}} + \delta_S' d_{\text{Seasonal}} + u_{it} \quad (13)$$

where $i = 1,\dots,N$, $t = 2,\dots,T$, u_{it} $i.i.d.$, y_{it} is the dependent variable, i.e. net margin, average spread, long spread, peso spread, UF spread, or dollar spread; $x_{i,t-2}$ is a vector of bank-specific explanatory variables, z_t is a vector of non bank-specific explanatory variables, $d_{\text{Asian Crisis}}$ and $d_{\text{Reg. Change}}$ are two events controlled by means of dummy variables, and d_{Seasonal} is a set of seasonal dummies. Finally, $\left[c,\alpha_i,\gamma_1,\beta,\phi,\delta_A,\delta_R,\delta_S\right]'$ is a vector of parameters, with α_i representing the Fixed-Effects. Notice that the bank-specific explanatory variables, i.e. those constructed from the information published by the SBIF, are included with two lags to account for the delay in this information to be publicly available. [50] Details regarding the estimation procedure are left to the Appendix.

IV. Results

Our analysis of the results (table IV.1) will be organized in terms of the five groups of variables defined in section III[51]. As a brief overview, the major differences between the results based on balance sheet data and the results based on interest rate data arise in the areas of industry structure and macro/monetary policy issues.

BANK CHARACTERISTICS

The variable noninterest expenses, which is defined as the ratio of overhead costs minus net commissions divided by earning assets, is typically included in net margin regressions. These overhead costs and commissions must be covered by banks somewhere in their operations, so higher costs may be associated with higher spreads. On the other hand, higher costs may show up as lower profits with no correlation with spreads. To the extent that higher costs are indeed correlated with higher spreads, the correlation could reflect market power or it could reflect that high costs of operations are required to make higher-yielding loans (riskier or smaller loans). Table IV.1 indicates that the *NIM* and the Average Spread as well as two of the four interest rate spreads are positively correlated with noninterest expenses.

The *NIM* accounting identity (equation 2) predicts that bank equity capital should be positively correlated with the spread. On the other hand, the single-period profit-maximizing approach of the Monti-Klein model followed in equation (3) suggests that bank equity should be uncorrelated with the spread. Table IV.1 indicates that the sign of the regression coefficient on the capital/asset ratio is actually *negative* for all five

[50] Under certain circumstances, bank fundamentals may be endogenously determined. This lag structure mitigates the potential problem of endogeneity.

[51] For details, see table III.5.

measures of spreads, with significant coefficients for three of the spreads. This result may be consistent with an alternative maximizing approach in which the structure of the bank's balance sheet affects the incentives to take risk. Less capitalized banks have more incentive to take on additional risk (resulting in higher spreads) in order to gamble for high returns. On the other hand, more capitalized banks tend to make more conservative loans (resulting in lower spreads) because there is more shareholder capital at risk.

Asset quality is an index of loan portfolio risk that is calculated by the Superintendency of Banks. This *ex-ante* proxy for default risk is preferable to the *ex-post* measure provided by the ratio of non-performing loans to total loans. The regression results at first appear puzzling. While the peso spread increases with the risk index, the average spread decreases (as do three other spreads, although not statistically significantly). A plausible explanation is that deposit rates in Chile are sensitive to risk.[52] This factor would produce a negative correlation between asset quality and spreads that is shown in Table IV.1. If problems with asset quality are concentrated in peso loans, rather than in inflation-indexed or dollar loans, then the peso spread could simultaneously be positively correlated with the asset quality variable.[53]

Management efficiency (*Loans/Employees*) is measured by the ratio of total loans to the number of employees[54]. We find a negative and statistically significant relationship for the *NIM*, the average spread, and the dollar spread. A high value of loans per employee may reflect efficient processing of loans, or it may reflect the type of loan (e.g., large versus small). In either case, the negative sign is consistent with the industrial organization approach of the Monti-Klein model.

AGGREGATE RISK

We use interbank interest rate volatility as a proxy for liquidity (interest rate) risk faced by the banking industry. The parameter values are positive for all six spreads, and are significant for four out of the six. These results strongly confirm the predictions of the dealership model (where banks are modeled as if they were securities dealers) [55]. In addition to interest rate risk, we use exchange rate volatility as a proxy for exchange rate risk. The results are similar, except that increased exchange rate uncertainty is correlated with a *smaller* spread on dollar operations.

INDUSTRY STRUCTURE

We find that the *NIM*, average spread, the peso spread, and the UF spread are positively correlated with bank size. These results suggest that larger banks have market power that results in larger spreads. Alternatively, large banks may be operating at beyond optimal

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[52] See Brock and Rojas (2000) for corroborating evidence.
[53] Loans denominated in UF and dollars are generally higher quality than peso loans, many of which are either personal consumption loans or commercial loans for working capital.
[54] Thus, higher managerial costs should be shown up as a decrease on this ratio.
[55] See, for example, the original dealership model of Ho and Saunders (1981) or Angbazo's (1997) extensions of that model.

size.[56] Large bank size is also negatively correlated with the long spread (1-3 year peso loan rate minus 30-89 day peso deposit rate). Altering asset duration (as opposed to acting as a broker) is a significant source of income for banks. Banks are able to take on asset transformation risk, partly because they enjoy deposit insurance. The regression results show that large banks are more aggressive at maturity transformation (they charge a smaller premium). This could be because of better risk-management skills or because large banks fall into a "too big to fail" category that allows them to take this type of risk.

The sign of the parameter for branches is always negative except for the long spread. These mirror image results (compared to the results for bank size) suggest that banks with many branches compete more as brokers (implying lower spreads for peso, UF, and dollar matched operations) and are not as aggressive at asset transformation (implying a higher long spread).[57]

The third I/O type variable is concentration. The literature contains two opposite hypotheses regarding the impact of concentration on the pricing behavior of banks.[58] The structure-performance hypothesis (SPH) claims that a more concentrated banking industry will behave oligopolistically, while the efficient-structure hypothesis (ESH) claims that concentration will produce efficiency gains as more efficient banks take over less efficient ones. In terms of the Monti-Klein model, greater concentration should result in higher spreads, while enhanced efficiency (such as labor cost savings) should reduce spreads.

Our results show that the *NIM* and average spread *increase* with concentration, but that the peso, UF, and dollar spreads all *decrease* with concentration. This suggests that banks provide brokerage services (same maturity loan and deposit operations) at lower cost as concentration increases. However the positive effect of concentration on the *NIM* and Average Spread suggests that concentration also permits banks to increase other marginal spreads. For example, Fuentes and Basch (2000) have noted that Chilean banks frequently take risky positions with regard to movements in the exchange rate[59].

POLICY ISSUES

Interest rate margins and spreads respond to changes in monetary policy, the business cycle, and capital account controls. To capture the relation of spreads with monetary policy we use the slope of the yield curve. To capture the relationship of spreads with the business cycle we use the deviation of output from its long-term trend (output gap).

[56] Budnevich, Franken, and Paredes (2001) provides evidence that larger banks within the Chilean Banking System may actually be in a larger than optimum (horizontal and conglomerated) size, thereby incurring in diseconomies of scale or scope.

[57] Alternatively, the negative coefficients could suggest that bank branches provide efficiency gains. However, it is difficult to explain the sign of the long peso spread with that explanation.

[58] See Berger and Hannan (1989).

[59] We would like to warn our audience that we do not think this reduced form regression can provide a sophisticated view of the impact of concentration on the pricing behavior of banks. In order to extract policy implications about this issue, a more complete model of the market structure as well as the equilibrium conditions for different types of loans and deposits is needed. Such a model is beyond the scope of this paper, and is left for future research.

Finally, capital account controls are included by means of a composite index that summarizes restrictions on both inflows and outflows.

Both the *NIM* and the Average Spread are positively correlated with increases in the slope of the yield curve. The long spread is also positively correlated with the slope of the yield curve. In contrast, the peso and UF interest rate spreads are negatively correlated with the slope of the yield curve. These results suggest that a steeper yield curve increases the *NIM* and the Average Spread because these spreads reflect a mixture of long-term and short-term assets. However, the peso spread and UF spread are matched maturity (deposit and loan) spreads, and these spreads are negatively correlated with the slope of the yield curve.

A steep yield curve is often associated with expansionary monetary policy. Our empirical results suggest that banks benefit from expansionary monetary policy by higher spreads, an observation that has been noted in other contexts. Expansionary monetary policy allows banks more easily to take duration risk. On the other hand, our results suggest that banks do worse with matched maturity operations during periods of expansionary monetary policy. To our knowledge this result has not been noted before, but it suggests that a loosening of monetary policy may help banks that are actively engaged in term transformation while hurting banks that match loan and deposit maturities.

We find results for the output gap that come close to replicating those of the yield curve slope. In particular, the *NIM*, Average Spread, and long spread are all procyclical. Among the matched maturity spreads, the peso spread is also procyclical, while the UF and dollar spreads are countercyclical. To the extent that the slope of the yield curve is positively correlated with the output gap, then the similarity of the results is not surprising. Nevertheless, in the Chilean context it is useful to draw the parallel results.

Finally, among this group of variables, are capital account controls. The Central Bank of Chile imposed a capital control in the form of an unremunerated reserve requirement on selective capital inflows in 1991. This reserve requirement varied over time until September 1998, when it was abolished. Other quantitative and administrative controls on capital inflows and outflows were also relaxed during the 1990s. We capture this capital account controls by means of a composite index (outflows and inflows) constructed from the measures proposed by Gallego, Hernández and Schmidt-Hebbel (2002). According to their study, an increase in the unremunerated reserve requirement puts upward pressure on the deposit rate, thereby lowering spreads. [60] However other administrative and quantitative capital controls were related to outflows, so the overall effect in unclear. We found a negative and statistically significant relationship between capital controls and all spreads, except the Dollar spread. The positive and statistically significant parameter of the latter spread makes sense since capital controls on inflows and outflows restrict the substitutes of dollar transactions, thereby lowering competition in that market.

[60] This unremunerated reserve requirement increases the cost of external (foreign) funding by banks. Hence, in order to attract domestic funds banks have to raise deposits rates.

DUMMY VARIABLES

The Asian crisis began to unfold during the second half of 1997.[61] The dummy variable for the Asian crisis (0 through 1997:2, 1 from 1997:3 onward) produces virtually the identical impact on spreads as the capital controls variable. All spreads were negatively correlated with the Asian crisis dummy variable except the dollar spread, which was positive. The Asian crisis produced a sharp contraction of capital flows to Chile and the rest of Latin America. The empirical results indicate that restrictions on capital flows, whether by caused by controls or by external events, lower *NIM*s, Average Spreads, long spreads, and matched maturity spreads for pesos and UFs.

The compulsory inclusion of commissions in loan rates took place in mid-1999 for loans with maturity larger than 90 days and in the first quarter of 2000 for loans with a shorter maturity.[62] The *NIM* and average spread regressions do not include a dummy for the regulatory change, since commissions are already included in the calculation of these spreads. One should expect loan rates and spreads to increase after this regulatory change. This is exactly what we find for the Pesos and UF spreads. However, the parameter value for the dummy related the regulatory change is negative for the Dollar spread.

[61] It is important to say that such a period coincides with the sign-up and implementation of the Basel capital requirements by Chile. Although this regulatory change may also play a role in the magnitude, sign and statistical significance of this dummy variable, we believe that the Asian crisis plays a far more relevant role.
[62] They included some important changes in the way to calculate maximum loan rates.

Table IV.1: Results of the Regressions												
(Method: Bias Corrected Fixed effects, GLS-Weighted, WHC-Robust Cov. Matrix)												
	Accounting Data				Interest Rate Data							
	Net Margin		*Average Spread*		*Long Spread*		*Peso Spread*		*UF Spread*		*Dollar Spread*	
Net Margin$_{t-1}$	0,8758	*										
Average Spread$_{t-1}$			0,7965	*								
Long Spread$_{t-1}$					0,5938	*						
Peso Spread$_{t-1}$							0,4656	*				
UF Spread$_{t-1}$									0,3286	*		
Dollar Spread$_{t-1}$											0,6185	*
Implicit Payments$_{t-2}$	0,0293	**	0,0996	*	0,2749	***	-0,0047		0,0882	*	-0,0035	
(Capital/Asset)$_{t-2}$	-0,0020		-0,0114	*	-0,0380	***	-0,0008		-0,0164	*	-0,0066	
Asset Quality$_{t-2}$	0,0034		-0,0287	*	-0,0666		0,0130	*	-0,0160		-0,0122	
(Loans/Employees)$_{t-2}$	-0,0022	*	-0,0045	*	-0,0127		-0,0001		-0,0015		-0,0038	*
Interest Rate Volatility	0,0043	*	0,0243	*	0,0022		0,0120	*	0,0189	*	0,0073	
Exchange Rate Volatility	0,0005	*	0,0010	*	0,0046	**	0,0001		0,0005	*	-0,0014	*
Size$_{t-2}$	0,0053	*	0,0122	*	-0,1958	*	0,0028	*	0,0363	*	-0,0105	
Branches$_{t-2}$	-0,0011	*	-0,0019	*	0,0117	**	-0,0007	*	-0,0046	*	-0,0013	**
Concentration$_{t-2}$	0,0292	*	0,0415	*	0,0081		-0,0037	*	-0,0127	*	-0,0420	*
Slope of the Yield Curve	0,0100	*	0,0338	*	0,2638	*	-0,0144	*	-0,1244	*	0,0164	
Output Gap$_{t-6}$	0,0237	*	0,0337	*	0,2310	*	0,0047	*	-0,0549	*	-0,0471	*
Capital Controls	-0,0013	*	-0,0028	*	-0,0241	*	-0,0005	*	-0,0031	*	0,0108	*
Asian Crisis	-0,0853	*	-0,1593	*	-0,8824	*	-0,0287	*	-0,0286		0,2489	*
Regulatory Change					0,6901		0,0793	*	0,1489	*	-0,2656	*
Adjusted R-squared	0,5010		0,5588		0,4015		0,3151		0,7916		0,6720	

(*) 1% significance level
(**) 5% significance level
(***) 10% significance level
See Table III.3 for definitions of the variables.

V. Conclusions

Studies of bank spreads have generally relied on the net interest margin as the measure of the cost of intermediation. The availability of more disaggregated data has recently allowed researchers to explore other spreads. In particular, Catao's (1998) work on dual currency markets in Argentina and Corvoisier and Gropp's (2001) study of banking concentration in the European Union have demonstrated the value of disaggregated interest rate spreads for banking industry analysis.

In this paper we have calculated net interest margins (*NIM*s) and average spreads from balance sheet and income statements. In addition we have used individual bank data to calculate matched maturity spreads for Peso, UF, and Dollar operations as well as to construct a long spread (long-term Peso loan rate minus short-term Peso deposit rate). This is the first study to use individual bank interest rate data in conjunction with balance sheet data to study issues that affect the cost of financial intermediation.

We find that the matched maturity spreads are conceptually similar to bid-ask spreads in securities markets, an idea that was originally put forward by Ho and Saunders (1981). In contrast, the long spread captures the premium that banks charge for bearing duration risk. The brokerage function and term transformation functions of banks are blurred in the *NIM*s and Average Spreads, since all interest income and expenses are aggregated to create implicit returns on assets and liabilities. Nevertheless, the *NIM* and the Average Spread are important because aggregation highlights the overall profitability of bank management across different loan and deposit activities, as well as the role of noninterest income activities.

We find that the estimated impacts of industry concentration, business cycle variables, and monetary policy variables differ markedly between interest rate spreads based on balance sheet data and interest rate spreads based on disaggregated loan and deposit data. Since empirical work on interest spreads is used for guiding policy recommendations, these findings potentially have important implications for the interpretation of interest spreads regressions. Our analysis calls for some caution in the interpretation of estimated empirical determinants of bank spreads that are constructed from income statements and balance sheet data. At the same time, our analysis shows how implicit interest rate spreads constructed from balance sheets and income statements can be combined with disaggregated interest rate spreads to create a more complete portrait of bank behavior than either type alone is capable of creating. The results for Chile suggest the potential importance of gathering such disaggregated data in other countries.

REFERENCES

Agénor, P., Aizenman, J., and A. Hoffmaister (1999). "Contagion, Bank Lending Spreads and Output Fluctuations" *IMF Staff Papers*, June.

Ahumada, A. and C. Budnevich (1999). "Evaluación de la Fragilidad del Sistema Bancario en un Ambiente de Estabilidad: Chile 1990-1998" *Revista de Economía Chilena - Banco Central de Chile, 2 (2), 21-37.*

Alessie, R., S. Hochguertel, and W. Koeniger (2001). "Consumer Credit: Evidence from Italian Micro Data" *Manuscript*, EUI.

Allen, L. (1988). "The Determinants of Banks Interest Margins." *Journal of Business*, 62, 501-15.

Alonso-Borrego, C., and M. Arellano (1999). "Symmetrically Normalized Instrumental-Variable Estimation Using Panel Data." *Journal of Business and Economic Statistics*, 17, 36-49.

Angbazo, L. (1997). "Commercial Bank Net Interest Margins, Default Risk, Interest-Rate Risk, and Off-Balance Sheet Banking." *Journal of Banking and Finance*, 21, 55-87.

Arellano, M., and S. Bond (1991). "Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations." *The Review of Economic Studies 58*, 277-97.

Barajas, A., R. Steiner, and N. Salazar (1999). "Interest Spreads in Banking in Colombia, 1974-96." *IMF Staff Papers*, 46, 196-224.

Barajas, A., R. Steiner, and N. Salazar (2000). "The Impact of Liberalization and Foreign Investment in Colombia's Financial Sector." *Journal of Development Economics*, 63, 157-96.

Bennet, H., and R. Valdés (2001). "Serie de Términos de Intercambio de Frecuencia Mensual para la Economía Chilena: 1965-1999." *Working Paper Series Central Bank of Chile*, 99.

Berger, A., and T. Hannan (1989). "The Price-Concentration Relationship in Banking." *The Review of Economics and Statistics*, 71, 291-99.

Berger, A., and G. Udell (1992). "Some Evidence on the Empirical Significance of Credit Rationing." *Journal of Political Economy*, 100, 1047-77.

Bernanke, B. (1983). "Nonmonetary Effects of the Financial Crisis in the Propagation of the Great Depression." *American Economic Review*, 73, 257-76.

Bernanke, B., and A. Blinder. (1988). “Credit, Money, and Aggregate Demand.” *American Economic Review*, Papers and Proceedings, 78, 435-39.

Bernanke, B., and M. Gertler (1989). “Agency Costs, Net Worth, and Business Fluctuations.” *American Economic Review*, 79, 14-31.

Bernanke, B., and M. Gertler (1990). “Financial Fragility and Economic Performance.” *Quarterly Journal of Economics*, 105, 87-114.

Berstein, S. and R. Fuentes (2003). “De la Tasa de Política a la Tasa de Colocación Bancaria: La Industria Bancaria Chilena.” *Revista de Economía Chilena - Banco Central de Chile, 6(1), 48-67.*

Bertola, G., S. Hochguertel, and W. Koeniger (2002). “Dealer Pricing of Consumer Credit.” *Center for Economic Policy Research Discussion Paper*, 3160, London.

Bester, H. (1985). “Screening vs. Rationing in Credit Markets with Imperfect Information.” *American Economic Review*, 75(4), 850-55.

Bhattacharya, S., and A. Thakor (1993). “Contemporary Banking Theory.” *Journal of Financial Intermediation*, 3, 2-50.

Bollen, N., T. Smith, and R.Whaley (2003). “Modeling the Bid/Ask Spread: Measuring the Inventory-Holding Premium.” *Journal of Financial Economics*, forthcoming.

Brock, P., and L. Rojas-Suarez (2000). “Understanding the Behavior of Bank Spreads in Latin America.” *Journal of Development Economics*, 63, 113-34.

Budnevich, C., H. Franken, and R. Paredes (2001). “Economías de Escala y Economías de Ámbito en el Sistema Bancario Chileno.” *Revista de Economía Chilena - Banco Central de Chile*, 4, 59-74.

Catao, L. (1998). “Intermediation Spreads in a Dual Currency Economy: Argentina in the 1990’s.” *IMF Working Paper*, 98-90, May.

Cerasi, V., and S. Daltung (1994). “The Optimal Size of a Bank: Costs and Benefits of Diversification.” *FMG Discussion Paper*, London School of Economics, London.

Cetorelli, N., and M. Gambera (2001). “Banking Market Structure, Financial Dependence and Growth: International Evidence from Industry Data.” *Journal of Finance*, 16 (2), 617-48.

Choi, I. (2001a). “Unit Root Tests for Cross-Sectionally Correlated Panels.” *Manuscript*, Kookmin University, Seoul.

Choi, I. (2001b). “Unit Root Tests for Panel Data.” *Journal of International Money and Finance*, 20, 249-72.

Claessens, S., A. Demirguc-Kunt, and H. Huizinga (2001). “How Does Foreign Entry Affect Domestic Banking Markets?” *Journal of Banking and Finance*, 25, 891-911.

Corvoisier, S., and R. Gropp (2001). “Bank Concentration and Retail Interest Rates.” *Working Paper Series European Central Bank*, 72.

Demirguc-Kunt, A., and H. Huizinga (1999). “Determinants of Commercial Bank Interest Margins and Profitability: Some International Evidence.” *World Bank Economic Review*, 13, 379-408.

Demirguc-Kunt, Laven, and Levine (2003). “The Impact of Bank Regulations, Concentration, and Institutions on Bank Margins.” World Bank working paper, Washington, D.C.

Demsetz, H. (1968). “The Cost of Transacting.” *Quarterly Journal of Economics*, 82, 33-53.

Dermine, J. (1986). “Deposits Rates, Credit Rates, and Bank Capital: The Monti-Klein Model Revisited” *Journal of Banking and Finance*, 10, 99-114.

Diamond, D. (1984). “Financial Intermediation and Delegated Monitoring.” *Review of Economic Studies*, 51 (3), 393-414.

Fontaine, J. (1995). *Chile: La Construcción de un Mercado de Capitales*. World Bank.

Freixas, X. and J. Rochet. 1997. *Microeconomics of Banking*. Cambridge: MIT Press.

Fuentes, R. and M. Basch (2000). “Macroeconomic Influences on Bank Spreads in Chile, 1990-95.” In *Why So High? Understanding Interest Rate Spreads in Latin America*. Edited by P. Brock and L. Rojas-Suarez. Washington, D.C., Interamerican Development Bank.

Gallego, F., L. Hernández, and K. Schmidt-Hebbel (2002). “Capital Controls in Chile: Effective? Efficient?” In *Banking, Financial Integration, and International Crises*. Edited by L. Hernández and K. Schmidt-Hebbel. Central Bank of Chile.

Goldsmith, R. (1969). *Financial Structure and Development*. New Haven, Yale University Press.

Greenwood, J. and B. Smith (1997). “Financial Markets in Development, and the Development of Financial Markets.” *Journal of Economic Dynamics and Control*, 21 (1), 145-81.

Gurley, J. and E. Shaw (1960). *Money in a Theory of Finance*. Washington, D.C., Brookings Institution.

Hahn, J., J. Hausman, and G. Kuersteiner (2002). "Biased-Corrected Instrumental Variables Estimation for Dynamic Panel Models with Fixed Effects." *Manuscript*, MIT University.

Hahn, J., and G. Kuersteiner (2002). "Asymptotically Unbiased Inference for Dynamic Panel Models with Fixed-Effects when both N and T are Large." *Econometrica* (forthcoming).

Ho, T., and A. Saunders (1981). "The Determinants of Bank Interest Rate Margins: Theory and Empirical Evidence." *Journal of Financial and Quantitative Analysis*, 16(4), 581-600.

Holmstrom, B., and J. Tirole (1994). "Financial Intermediation, Loanable Funds, and the Real Sector." *Quarterly Journal of Economics*, 112 (3), 663-91.

Holtz-Eakin, D., W. Newey, and H. Rosen (1988). "Estimating Vector Autoregressions with Panel Data." *Econometrica*, 1371-95.

Honohan, P. (2003). *Taxation of Financial Intermediaries: Theory and Practice for Emerging Economies.* New York and Washington, D.C., Oxford University Press and the World Bank.

Im, K., H. Pesaram, and Y. Shin (1997). "Testing for Unit Roots in Heterogeneous Panels." *Manuscript*, University of Cambridge.

King, R. and R. Levine (1993). Finance and Growth: Schumpeter Might Be Right. *Quarterly Journal of Economics*, 108 (3), 717-37.

Klein, M. (1971). "A Theory of the Banking Firm." *Journal of Money, Credit, and Banking*, 3, 205-18.

Lerner, E. (1981). "Discussion: The Determinants of Bank Interest Rate Margins: Theory and Empirical Evidence." *Journal of Financial and Quantitative Analysis*, 16(4), 601-603.

Levin, A., and C. Lin (1992). "Unit Root Tests in Panel Data: Asymptotic and Finite Sample Properties." *Manuscript*, University of California, San Diego.

Levine, R. (1997). "Financial Development and Economic Growth: Views and Agenda." *Journal of Economic Literature*, 35, 688-726.

McKinnon, R. (1973). *Money and Capital in Economic Development*. Washington, D.C., The Brookings Institution.

McShane, R., and I. Sharpe (1985). "A Time Series/Cross Section Analysis of the Determinants of Australian Trading Bank Loan/Deposit Interest Margins: 1962-1981." *Journal of Banking and Finance*, 9, 115-36.

Mercer, Z. (1992). "Valuing Financial Institutions (Business One Irwin, Homewood, IL).

Merton, R. (1974). "On the Pricing of Corporate Debt: The Risk Structure of Interest Rates." *Journal of Finance*, 29, 449-70.

Monti, M. (1972). "Deposits, Credit, and Interest Rate Determination Under Alternative Bank Objectives." In *Mathematical Methods in Investment and Finance.* Edited by G. Szego and K. Shell. Amsterdam: North Holland.

Morandé, F. (2002). "A Decade of Inflation Targeting in Chile: Developments, Lessons, and Challenges." In *Inflation Targeting: Design, Performance, and Challenges.* Edited by N. Loayza and R. Soto. Central Bank of Chile.

Neumark, D., and S. Sharpe (1992). "Market Structure and the Nature of Price Rigidity: Evidence from the Market for Consumer Deposits." *Quarterly Journal of Economics*, 107, 657-80.

Petersen, M. and R. Rajan (1994). "The Benefits of Lending Relationships: Evidence from Small Business Data." *Journal of Finance*, 49 (1), 3-37.

Prisman, E., M. Slovin, and M. Sushka (1986). "A General Model of the Banking Firm Under Conditions of Monopoly, Uncertainty, and Recourse." *Journal of Monetary Economics*, 17(2), 293-304.

Rajan and Zingales (1998). "Financial Dependence and Growth." *American Economic Review*, 88(3), 559-86.

Ruthenberg, D., and R. Elias (1996). "Cost Economies and Interest Rate Margins in a Unified European Banking Market." *Journal of Economics and Business*, 48, 231-49.

Saunders, A., and L. Schumacher (2000). "The Determinants of Bank Interest Rate Margins: An International Study." *Journal of International Money and Finance*, 19, 813-32.

Schumpeter, J. (1911). *Theory of Economic Development: An Inquiry into Profits, Capital, Credit, Interest and the Business Cycle.*

Sinkey, J., and D. Carter. (2000). "Evidence on the Financial Characteristics of Banks that do and do not Use Derivatives." *Quarterly Review of Economics and Finance*, 40, 431-49.

Smith, Adam (1776). *An Inquiry into the Nature and Causes of the Wealth of Nations*. Republished from Edwin Cannan's annotated edition, 1904, Methuen & Co., Ltd., reproduced at http://www.econlib.org/library/Smith/smWN.html.

Spiller, P. and E. Favaro (1984). "The Effects of Entry Regulation on Oligopolistic Interaction: The Uruguayan Banking Sector." *RAND Journal of Economics*, 15 (2), 244-54.

Stiglitz, J. and A. Weiss (1981). "Credit Rationing in Markets with Imperfect Information." *American Economic Review*, 71 (3), 393-410.

Stoll, H. (1978). "The Pricing of Security Dealer Services: An Empirical Study of NASDAQ Stocks." *Journal of Finance*, 33 (4), 1153-72.

Stoll, H. (1989). "Inferring the Components of the Bid-Ask Spread: Theory and Empirical Tests." *Journal of Finance*, 44 (1), 115-34.

Stoll, H. (2003). "Market Microstructure." In Constantinides, G., M. Harris, and R. Stultz (eds.), *Handbook of the Economics of Finance*, Amsterdam, North-Holland (forthcoming).

Williams, B. (1998). "Factors Affecting the Performance of Foreign-Owned Banks in Australia: A Cross-Sectional Study." *Journal of Banking and Finance*, 22, 197-219.

Williamson, S. (1987). "Financial Intermediation, Business Failures, and Real Business Cycles. *Journal of Political Economy*, 95, 1196-1216.

Wong, K. (1997). "On the Determinants of Bank Interest Margins Under Credit and Interest Rate Risks." *Journal of Banking and Finance*, 21, 251-71.

Appendix

A1. Estimation Procedure

Most of the empirical literature constraints γ_1 in (13) to be equal to zero, i.e. does not include a lag dependent variable. They are implicitly assuming that all regressors are strictly exogenous. Such an assumption in the fixed T-large N asymptotic framework is fundamental for the consistency of the Fixed-Effects estimator. The following example will help to see why. Suppose $T=3$ and the simpler version of the model $y_{it}=\gamma y_{i,t-1}+\alpha_i+u_{it}$ with u_{it} $i.i.d.$ Thus, to get the within (fixed-effects) estimator we regress $(y_{i3}-y_{i2})$ on $(y_{i2}-y_{i1})$. That is to say, $(y_{i3}-y_{i2})=\gamma(y_{i2}-y_{i1})+(u_{i3}-u_{i2})$. It is clear that this is not longer a well-structured model since y_{i2} contains u_{i2} by definition. Hence, they are correlated. It can be shown, in this particular case[63], that $\text{Plim}\,\hat{\gamma}=\left[\frac{\gamma-1}{2}\right]$. We can see that the Fixed-Effects estimator in a dynamic context is severely biased. Such a bias decreases as T increases. But, since we are still in the fixed T-large N asymptotic framework, there is no way to fix the problem.

The origin of the problem is the presence of a weakly exogenous regressor. In the more general model $y_{it}=\beta x_{it}+\gamma y_{i,t-1}+\alpha_i+u_{it}$, x_{it} is assumed to be strictly exogenous, i.e. $E\left[\begin{pmatrix}x_{i1}\\ \vdots \\ x_{iT}\end{pmatrix}\begin{pmatrix}u_{i1} & \dots & u_{iT}\end{pmatrix}\right]=0$, but $y_{i,t-1}$ is weakly exogenous, i.e. $E\left[\begin{pmatrix}y_{i1}\\ \vdots \\ y_{i,t-1}\end{pmatrix}u_{it}\right]=0$.

As noted by Holtz-Eakin, Newey and Rosen (1988), such feature suggests a natural instrument. First differencing the model to remove α_i produces the model

$$(y_{it}-y_{i,t-1})=(x_{it}-x_{i,t-1})\beta+(y_{it}-y_{i,t-1})\gamma+(u_{it}-u_{i,t-1})$$

which is estimable by instrumental variables.

Assuming, $u_{it},u_{i,t-1}\perp y_{i,t-2},y_{i,t-3},\ldots\Rightarrow u_{it}-u_{i,t-1}\perp y_{i,t-2},y_{i,t-3},\ldots$, the set of instruments is:

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[63] The sketch of the proof is the following: start from

$$\hat{\gamma}=\frac{N^{-1}\sum_i(y_{i3}-y_{i2})(y_{i2}-y_{i1})}{N^{-1}\sum_i(y_{i2}-y_{i1})^2}\rightarrow\frac{E\left[(y_{i3}-y_{i2})(y_{i2}-y_{i1})\right]}{E\left[(y_{i2}-y_{i1})^2\right]}$$

i.e. $$\text{Plim}\,\hat{\gamma}=\gamma+\frac{E\left[(y_{i2}-y_{i1})(u_{i3}-u_{i2})\right]}{E\left[(y_{i2}-y_{i1})^2\right]}=\gamma-\frac{\sigma_u^2}{E\left[(y_{i2}-y_{i1})^2\right]}$$

Finally, work backwards from $y_{it}=\gamma y_{i,t-1}+\alpha_i+u_{it}$.

$$E\left\{\left(u_{it}-u_{i,t-1}\right)\begin{pmatrix} x_{i1} \\ \vdots \\ x_{iT} \\ y_{i0} \\ y_{i1} \\ \vdots \\ y_{i,t-2} \end{pmatrix}\right\}=0$$

Notice that the set of instruments is increasing over time. Hence, there should be enough instruments for consistent estimation of γ and β. Arellano and Bond (1991) worked with this idea within the GMM framework and realized that there is a potentially very large instrument matrix[64].

So, the Arellano and Bond GMM procedure is common used when estimating a dynamic panel model within the fixed T-large N asymptotic framework. However, with larger T, there is a potential problem with the over-identifying restrictions, since GMM estimators with too many over-identifying restrictions may perform poorly in small samples[65]. Moreover, as noted by Hahn, Hausman and Kuersteiner (2002), if a numerically identically minimum distance estimator is considered, it becomes crystal clear that the GMM estimator is equivalent to a linear combination of 2SLS estimators. The latter has long been known to be subject to substantial finite sample bias.

Notice, however, that in our particular application, the fixed T-large N asymptotic framework is not very appropriate. An alternative framework, which is likely to be more appropriate, is to assume the following asymptotic approximation: $0<\lim\frac{N}{T}<\infty$. Hahn and Kuersteiner (2002) show that under this alternative asymptotic approximation the Maximum Likelihood (which is equivalent to the OLS) estimation of a dynamic panel data model with Fixed-Effects is consistent and asymptotically normal, although it is not centered at the true value of the parameter. The non-centrality parameter captures bias of order $O(T^{-1})$. However, they proposed a bias-corrected estimator by examining the non-centrality parameter[66], and by showing that the bias-corrected MLE is asymptotically efficient. An algorithm to estimate a bias-corrected dynamic panel data model with Fixed-Effects in a multivariate context is included in appendix A2.

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[64] This matrix does not only include lagged levels of the dependent variable, but also lagged levels of predetermined variables (i.e. variables for which the error term at time *t* has some feedback on the subsequent realizations of it) and differences of strictly exogenous regressors.

[65] It has been found that the standard GMM estimators suffer from substantial finite sample biases. See Alonso-Borrego and Arellano (1999).

[66] For the univariate model $y_{it}=\gamma y_{i,t-1}+\alpha_i+u_{it}$ they show that the bias-corrected estimator is $\hat{\hat{\theta}}=\frac{T+1}{T}\hat{\theta}+\frac{1}{T}$ where $\hat{\theta}$ is the MLE (OLS) Fixed-Effects estimator.

There is one important *caveat* to this relatively simple solution: under unit root the bias-corrected estimator will not be (approximately) unbiased. We performed the unit root tests proposed by Choi (2001a), which are the following:

1. $P = -\frac{1}{\sqrt{N}} \sum_{i=1}^{N} \left(\ln(p_i) + 1 \right)$
2. $Z = \frac{1}{\sqrt{N}} \sum_{i=1}^{N} \Phi^{-1}(p_i)$
3. $L^* = \sqrt{\frac{1}{\pi^2 \frac{N}{3}}} \sum_{i=1}^{N} \ln\left(\frac{p_i}{1 - p_i} \right)$

where *N* is the number of cross-sectional units included in the panel, p_i is the p-value of a unit root test[67] and $\Phi(\bullet)$ is the standard normal cumulative distribution function. These tests have an asymptotic standard normal distribution.[68]

Given the absence of a unit root for our dependent and independent variables, as we concluded from the previous exercise, we follow the methodology proposed by Hahn and Kuersteiner.[69]

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[67] Choi recommends using the Dickey-Fuller-GLS$^{\mu}$ test.

[68] There are other unit root tests for Panel Data in the literature, such as the ones proposed by Im, Pesaram, and Shin (1997) and Levin and Lin (1992). However, Im et al. show that their tests have better finite sample performances compared to those proposed by Levin and Lin, as well as, Choi (2001b) shows that his tests outperform Im et al. tests in finite samples. Therefore, we concentrate only in the above three tests proposed by Choi.

[69] The results of the tests are available upon request.

A2. An Algorithm for Obtaining Bias-Corrected estimates in a Dynamic Panel Data Model with Fixed-Effects[70]

Suppose you have the following model:

$$y_{it} = c + \alpha_i + \gamma_1 y_{i,t-1} + \beta x_{i,t} + u_{it}$$

where $i = 1,\dots,N$, $t = 2,\dots,T$, x_{it} is an strictly exogenous regressor and u_{it} $i.i.d.$.

1. Eliminate individual effects by subtracting individual means

$$y_{it} - \bar{y}_i = \gamma_1 \left(y_{i,t-1} - \bar{y}_{i-} \right) + \beta \left(x_{it} - \bar{x}_i \right) + \left(u_{it} - \bar{u}_i \right)$$

where, $\bar{y}_i = (T-1)^{-1} \sum_{t=2}^{T} y_{it}$, $\bar{y}_{i-} = (T-1)^{-1} \sum_{t=2}^{T} y_{i,t-1}$, and $\bar{x}_i = (T-1)^{-1} \sum_{t=2}^{T} x_{it}$.

2. Run the regression

$$y_{it} - \bar{y}_i = \theta_1 \left(x_{it} - \bar{x}_i \right)$$

and call the residuals $\hat{y}_{it}$.

3. Run the regression

$$y_{i,t-1} - \bar{y}_{i-} = \theta_2 \left(x_{it} - \bar{x}_i \right)$$

and call the residuals $\hat{y}_{i,t-1}$.

4. Run the regression

$$\hat{y}_{it} = \gamma_1 \hat{y}_{i,t-1}$$

using the residuals of the two previous regressions.
Call the estimator from this regression $\hat{\gamma}_1$.

5. Apply the bias correction to $\hat{\gamma}_1$ such that:

$$\hat{\hat{\gamma}}_1 = \frac{T+1}{T} \hat{\gamma}_1 + \frac{1}{T}$$

This is now your bias-corrected estimate of γ_1.

6. Define $z_{it} = y_{it} - \bar{y}_i - \hat{\hat{\gamma}}_1 \left(y_{i,t-1} - \bar{y}_{i-} \right)$ and run the regression $z_{it} = \beta \left(x_{it} - \bar{x}_i \right)$ to obtain an estimate of β.

[70] We are thankful to Jinyong Hahn for sending us copies of his cited co-authored papers and to Guido Kuersteiner for providing us with this relatively simple algorithm.