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Factor Model for Stress-testing with a Contingent Claims Model of the Chilean Banking System

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Factor Model for Stress-testing with a Contingent Claims Model of the Chilean Banking System

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Abstract

This paper derives risk indicators for the major Chilean banks based on contingent claims analysis, an extension of Black-Scholes-Merton option-pricing theory. These risk indicators are clearly tied to macroeconomic and financial developments in Chile and outside, but bank responses are highly heterogeneous. To reduce the number of variables linked to the banks' risk to a tractable number, we apply principal component analysis. Vector autoregressions of risk indicators with the most significant factors show strong ties from financial markets and regional developments. Impulse response functions from these factors are derived, which allow for scenario testing. The scenarios derived in the paper illustrate how the magnitude and persistence of responses of bank credit risk can vary across banks in the system.

JEL Classification Numbers:

Keywords: contingent claims analysis, credit risk, factor model, VAR

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I. INTRODUCTION

The vulnerability of financial to macroeconomic and financial shocks is an area of important and growing interest to policymakers, especially in emerging markets. However, estimating the effect of such shocks on the risk of banks in a coherent manner requires both a model of banking sector risk and a tractable methodology for simulating shocks and estimating their effect on various risk measures.

This paper uses contingent claims analysis (CCA) tools developed in finance to estimate the riskiness of banks. The basis of the CCA methodology is the estimation of the probability that an entity (in our case, banks, but also corporations or even governments) will default on its obligations. Additional measures include the expected loss to the holders of the bank's debt, and also a measure of the financial fragility of the bank based on the distance, measured in the standard deviation of asset returns, that a bank's assets exceed its liabilities. The CCA is widely used by financial practitioners such as Moody's KMV to estimate the creditworthiness of corporates, and is highly correlated both with the ratings assigned by such agencies as well as with historic probabilities of default.

Due to its explicit focus on risk and probability and its basis on market-sourced data on equity prices, debt, and interest rates, CCA has many advantages. Equity data by nature incorporate the forward-looking expectations of the market in a way that static indicators of bank risk, such as nonperforming loan ratios and provisioning cannot, and the high frequency of observations, at least for equity and interest rate data, allow for much faster updating of risk measures than data available only at monthly or quarterly frequencies.

After deriving the risk measures provided under the CCA model, this paper assesses how various macroeconomic and financial variables in Chile affect them. One immediate result is that banks even in a relatively small emerging market such as Chile display a high degree of heterogeneity: the correlation of estimated risk measures with historic values of macroeconomic variables differ not only in magnitude but even in sign across the various banks, limiting the usefulness of a systemic approach that constrains the manner in which these shocks are propagated to be similar across banks. Beyond this, some variables which appear strongly correlated with the riskiness of one bank will have little or no correlation with the riskiness of others, necessitating the inclusion of a large number of variables in order to assess adequately the riskiness of all the banks in our sample.

As tractability is reduced by including such an exhaustive sample of variables, we reduce the size of this state space through principal component analysis. As some variables commove in expected ways, we are able to drop those variables with minor fluctuations only marginally related to some of the macro variables, and retain four significant factors that account for the largest share of the variance of all the macro variables.

The risk measures (or more specifically, the implied asset output of the CCA that underlies these measures) and the derived data from the principal components analysis are then plugged into a standard vector autoregression and impulse-response function model that allows for scenario analysis. The impulse response functions thus calculated yield various insights about how various macroeconomic factors impact the default risk of banks, and how the timing of both the maximum impact of shocks as well as the recovery from them can differ across banks.

The paper assesses the impact of shocks of magnitudes similar to those observed in Chile over the past 10 years on the risk measures of the banks in the sample, showing that the riskiness of Chilean banks has declined to historically low levels, and that even under shocks of magnitude similar to those seen in recent periods of financial turmoil, banks appear unlikely to reach the high levels of risk associated with the 1998 financial crisis.

Section II presents the background of the CCA model, and Section III discusses the data used in the analysis. Section IV presents the results of the CCA analysis and its extension via principal-components analysis to macro and financial shocks, and Section IV presents possible extensions in this line of research. Section V concludes.

II. Risk Measures from Contingent Claims Analysis

A. Background

The contingent claims approach (CCA) provides a methodology to combine balance sheet information with widely used finance and risk management tools to construct marked-to-market balance sheets that better reflect underlying risk. The risk adjusted balance sheets use option pricing tools to value the liabilities which are modeled as claims on stochastic assets. It can be used to derive a set of risk indicators that can serve as barometers of risk for firms, financial sector vulnerability, and sovereign risk.

A contingent claim is any financial asset whose future payoff depends on the value of another asset. The prototypical contingent claim is an option—the right to buy or sell the underlying asset at a specified exercise price by a certain expiration date. A call is an option to buy; a put is an option to sell and the value of each is contingent on the price of the underlying asset to be bought or sold. Contingent claims analysis is a generalization of the option pricing theory pioneered by Black-Scholes (1973) and Merton (1973). Since 1973, option pricing methodology has been applied to a wide variety of contingent claims. In this paper we focus on its application to the analysis of credit risk and guarantees against the risk of default, and their links to macroeconomic and financial developments.

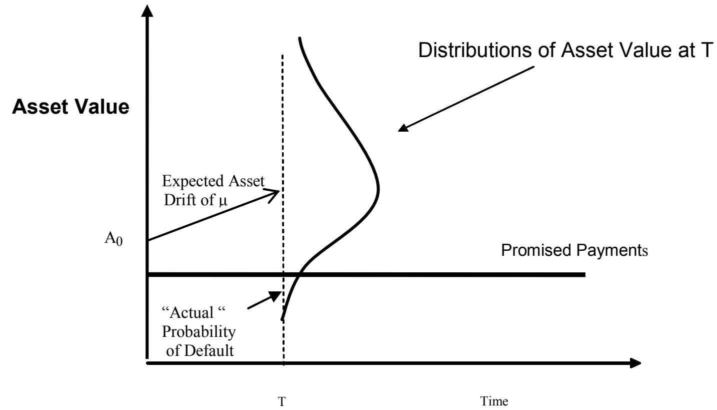
The contingent claims approach is based on three principles: (i) the values of liabilities are derived from assets; (ii) liabilities have different priority (i.e. senior and junior claims); and, (iii) assets follow a stochastic process. The liabilities consist of senior claims (such as senior debt), subordinated claims (such as subordinated debt) and the junior claims (equity or the most junior claim). For a bank, as the value of its total assets decline, the debt that it owes to other institutions becomes riskier, and its value declines, while and credit spreads on its risky debt rise.

Balance sheet risk is the key to understanding credit risk and crisis probabilities. Default happens when assets cannot service debt payments, that is, when assets fall below a distress barrier comprising the total value of the firm's liabilities. Uncertain changes in future asset value, relative to promised payments on debt, is the driver of default risk. Figure 1 illustrates the key relationships. The uncertainty in asset value is represented by a probability distribution at time horizon T. At the end of the period the value of assets may be above the promised payments indicating that debt service can be made, or below the promised payments leading to default. The area below the distribution in Figure 1(a) is the "actual" probability of default. The asset-return probability distribution used to value contingent claims is not the "actual" one but the "risk-adjusted" or "risk-neutral" probability distribution, which substitutes the risk-free interest rate for the actual expected return in the distribution. This risk-neutral distribution is the dashed line in Figure 1(b) with expected rate of return r, the risk-free rate. Thus, the "risk-adjusted" probability of default calculated using the "risk-neutral" distribution is larger than the actual probability of default for all assets which have an actual expected return (μ) greater than the risk-free rate r (that is, a positive risk premium).[1]

The calculation of the actual probability of default is outside the CCA/Merton Model but such a probability can be calculated by combining the CCA/Merton model with an equilibrium model of underlying asset expected returns to produce estimates that are consistent for expected returns on all derivatives, conditional on the expected return on the asset. One does not have to know expected returns to use the CCA/Merton models for the purpose of value or risk calculations, but for calibration into actual probabilities such data are necessary. The value of assets at time t is *A(t)*. The asset return process is $dA/A = \mu_A dt + \sigma_A \varepsilon \sqrt{t}$, where μ_A is the drift rate or asset return, σ_A is equal to the standard deviation of the asset return, and ε is normally distributed, with zero mean and unit variance. The probability distribution at time T is shown in (a) below.

[1] See Merton (1992, pp.334-343; 448-450).

Figure 1. Distribution of Asset Value



Default occurs when assets fall to or below the promised payments, B_t. The probability of default is the probability that $A_t \le B_t$ which is:

$$\text{Prob}(A_t \le B_t) = \text{Prob}\left(A_0 \exp\left[\left(\mu_A - \sigma_A^2/2\right)t + \sigma_A \varepsilon \sqrt{t}\right] \le B_t\right) = \text{Prob}\left(\varepsilon \le -d_{2,\mu}\right)$$

Since $\varepsilon \sim N(0,1)$, the "actual" probability of default is $N(-d_{2,\mu})$,

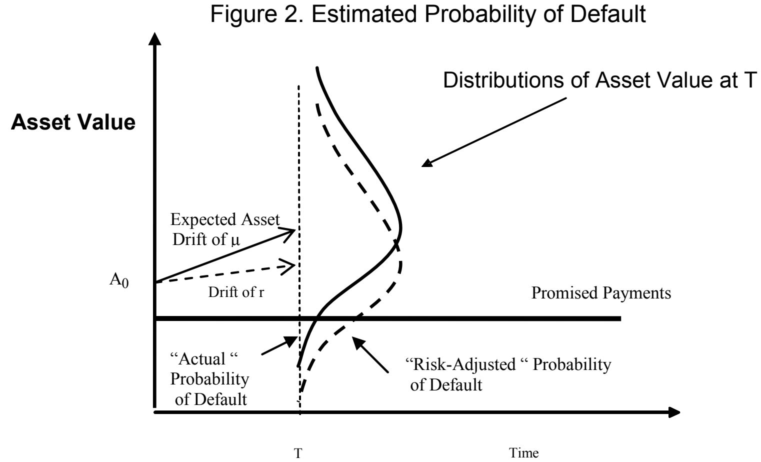
where $d_{2,\mu} = \dfrac{\ln\left(A_0/B_t\right) + \left(\mu_A - \sigma_A^2/2\right)t}{\sigma_A\sqrt{t}}$. This is distance to distress with drift of mu. $N(\cdot)$ is the cumulative standard normal distribution.

Shown in (b) below is the probability distribution (dashed line) with drift of the risk-free interest rate, r. Risk adjusted probability of default is $N(-d_2)$, where

$d_2 = \dfrac{\ln\left(A_0/B_t\right) + \left(r - \sigma_A^2/2\right)t}{\sigma_A\sqrt{t}}$. This is distance to distress with drift of r, the risk-free rate.

See Annex for more information on the Merton Model, how to link actual and risk-adjusted probabilities of default, and extension of the CCA model.

Figure 2. Estimated Probability of Default



Financial fragility is intimately related to probability of default. Shocks to prices or liquidity frequently end up being converted into credit risk in a crisis as banks' debtors income flows weaken and they run into difficulties servicing their loans to banks. Default is hard to handle in traditional macro models in part due to assumptions which usually exclude the possibility. In addition, flow-of-funds and accounting balance sheets cannot provide measures of risk exposures which are forward-looking estimates of losses. CCA, on the other hand, is a framework that explicitly includes and estimates the probability of default.

Since there is a nonzero chance of default, the value of debt is risky and therefore less than the value of riskfree debt:

Risky debt + guarantee against default ≡ Risk-free debt

The value of "risky" debt can therefore be modeled as the default-free value of the debt less the expected loss:

Risky debt ≡ Risk-free debt—Guarantee Against Default

Since this guarantee is an asset of uncertain value the debt can be thought of and modeled as a contingent claim.

This identity holds both conceptually and in terms of value. If the debt is collateralized by a specific asset, then the guarantee against default can be modeled as a put option on the asset with an exercise price equal to the face value of the debt. The debt holder is offering an implicit guarantee as it is obligated to absorb the losses if there is default. However, often a third party is the guarantor, as is the case when government guarantees the deposit liabilities of banks or the pension-benefit promises of firms.[2]

Using the Black-Scholes-Merton differential equation for pricing contingent claims, the value of risky debt is a function of the default free value of debt (i.e. distress barrier) at time 0, asset level at time 0, volatility of the asset, the time horizon until the expiration date of the claim, and the risk-free interest rate. Since 1973, the Merton Model methodology has been applied to a wide variety of contingent claims.

B. Calculating Risk Indicators for Individual Banks or Financial Institutions

Domestic equity markets provide pricing and volatility information for the calculation of implied assets and implied asset volatility in corporate, bank and non-bank financial institutions. The simplest method solves two equations for two unknowns, asset value and asset volatility. Details are shown in Annex I and in Merton (1974) and Crouhy et. al. (2000). Levonian (1991) used explicit option prices on bank equity to measure equity volatility and

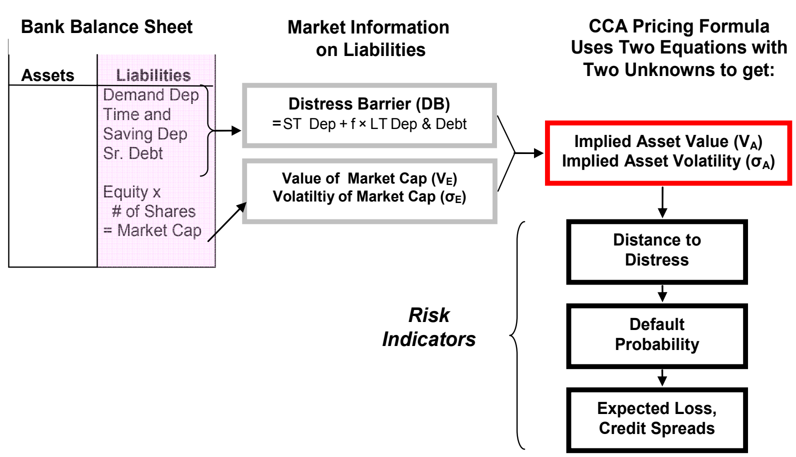
[2] The CCA framework is an extension of Merton's models of risky debt (1974) and deposit insurance (1977).

calibrate Merton Models for banks. Moody's-KMV has successfully applied its version of the CCA model to measure the implied assets values and volatilities and to calculate expected default frequencies (EDFs) for over 35,000 firms and financial institutions in 55 countries around the world KMV (1999 and 2001).

For unlisted corporates and banks, the relationship between the accounting information and the risk indicators, of companies with traded equity, can be used as a guide to map accounting information of companies without traded equity to default probabilities and risk indicators for institutions that do not have traded equity. (An example is Moody's RiskCalc for corporate sectors in many countries and for banks in the U.S.)

The CCA model for banks and financial institutions uses a time series of the daily market capitalization the volatility of the market capitalization, and the distress barrier (derived from book values of deposits and debt) to estimate a time series of the implied market value of bank assets and asset volatility. Several useful risk indicators can be calculated for each bank or institution: (i) distance to distress; (ii) the risk adjusted and actual probabilities of default; (iii) the expected losses (put option) to depositors and debt holders; (iv) potential size of financial guarantees of the public sector; and, (v) sensitivity of risk indicators to changes in underlying bank assets, asset volatility or other factors. The steps used to calculate the implied assets and asset volatility of the individual bank or financial institution, and the risk indicators, is shown in Figure 3.

Figure 3: Calibrating Bank CCA Balance Sheets and Risk Indicators



C. Data

Derivation of CCA risk indicators can be done at any frequency, but this paper uses daily data when available. Daily market capitalization data for the various banks were obtained by the Central Bank of Chile from the Bolsa de Santiago. Bank debt was obtained from the Central Bank of Chile's database.

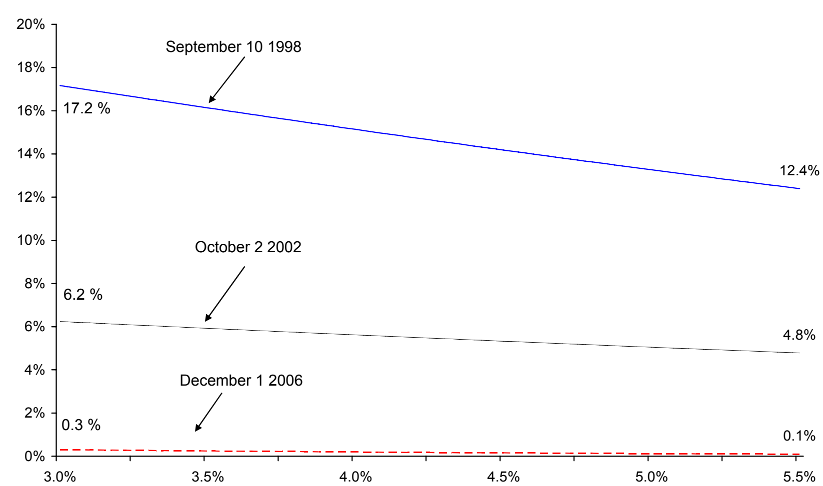
Some judgment was used in estimating the default barrier and interest rate used in the calculations. Practitioners do not generally set the default barrier equal to the total book value of a company's debt. Since longer-term debt can often be restructured, the default barrier is most frequently calculated as the sum of short-term debt and a share of long-term debt, in this paper, 50 percent. The choice of this parameter naturally has some impact on the results, but this effect is generally minor.

A more serious concern about the choice of default barrier is whether the threshold of interest is in fact default. Banks rarely default, and regulators are likely to be interested less in the probability of such an event than they are in the possibility that bank assets will fall below a level at which the authorities might be expected to intervene, or at which depositors might panic. However, such a "distance to distress" measure would require another assumption about what level assets would have to reach to warrant distress. One such assumption would be to estimate the level of assets implied by the CCA consistent with a minimum level of regulatory capital. This issue is discussed in Section IV below.

The choice of interest rate is also not straightforward. The assumption under the Black-Scholes model is of a risk-free rate. In the Chilean context, where the sovereign is not AAA and thus no bank is either, the choice of risk-free rate is not straightforward. For this paper, a constant fixed rate of 5 percent is assumed.

This fixed-rate assumption, while not realistic, is not uncommon in financial-market contexts. Moreover, for relatively low-risk situations, such as Chilean banks during all bit high-volatility periods, the sensitivity of default measures to interest rate shifts is minor. During high volatility periods, moreover, while the sensitivity to the value of the interest rate does rise, other components (such as rising equity volatility) have an equally large impact, and the misspecification of the interest rate will not fundamentally affect the conclusion of higher bank risk. Figure [4] below shows the default probability of one of the banks in our sample at three different points.

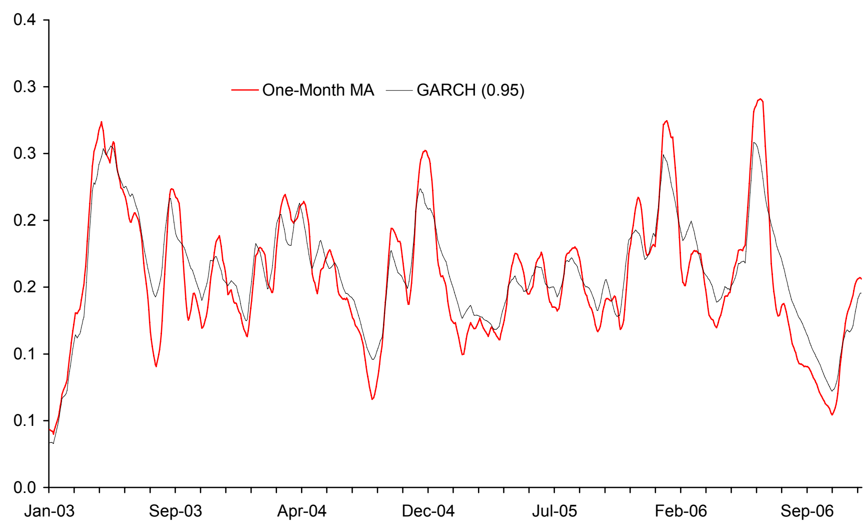
Figure 4. Estimated Risk-Neutral Default Probabilities for Bank 2
Under Varying Risk-Free Rate Assumptions



While the estimated (risk- neutral) default probabilities vary strongly based on the value of the riskfree rate for the high-risk period around the LTCM/Russia crisis in 1998, even the lowest default value based on a relatively high riskfree rate is quite high. During less active periods, such as late 2006, the interest rate makes less of a difference.

Finally, financial practitioners use various methods for estimating the volatility of daily asset returns. Two frequently used methods model daily volatility either as a GARCH(1,1) or as a moving average process. This paper uses the GARCH(1,1) methodology for all banks in the sample, but the results of the moving-average model are similar. Figure 5 below shows the daily estimated volatility for Bank 2 under both volatility assumptions.

Figure 5. 10-Day Moving Averages of Volatility Measures
for Changes in Stock Price of Bank 2



Section IV below discusses other ways in which both the interest rate and the volatility may be modeled more accurately.

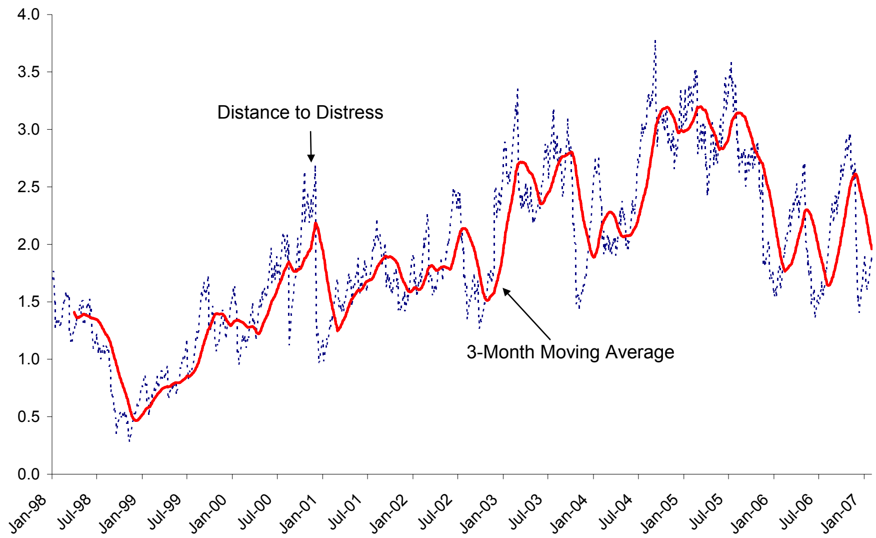
D. Banking Risk Indicators

As noted above, using daily price data and debt data (quarterly or monthly debt data is used to calculate the distress barrier) for major banks or financial institutions, the CCA model can be used to derive a time series of CCA risk indicators for individual banks and financial institutions and time series of more aggregate systemic risk indicators.

Distance-to-distress

A useful indicator of banking or financial sector risk over time is a graph of average distance-to-distress (DTD) where $DTD = d_2$ from Figure 1. Figure 6 shows the estimated time pattern of DTD for the Chilean banking system from 1998 to 2007, along with a three-month moving average. It was calculated by treating the portfolio of banks in the system as one "big bank" and estimating implied assets, implied asset volatility, and distance-to-distress. This procedure used historical volatility of market capitalization calculated with GARCH(1,1).

Figure 6. Distance to Distress Indicator of Financial Fragility



It is clear that the highest-risk period was in late 1998 and early 1999, during the fallout from the LTCM/Russia crisis. Since then the Chilean banking system has gradually reduced its risk, though this trend appears to have leveled off in late 2005.[3] Other periods where markets assessed suddenly higher risk for Chilean banks are easily discerned, for example, the decline in world stock markets following the collapse of the internet bubble in 2000 and the period preceding the Brazilian presidential elections in the third quarter of 2002.

Risk-neutral default probabilities

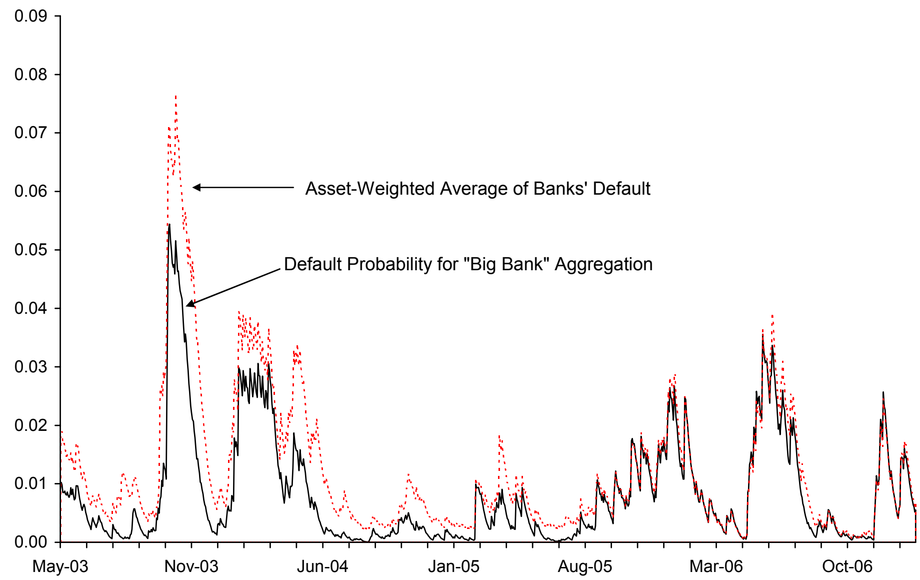
The Merton model can also produce the risk-neutral default probability for each of the financial institutions analyzed. Using the methodology laid out above the model produces the cumulative probability over the time period T that the institution will default, for which we assume one year. As noted above, this default probability is not the same as the real-world probability of default. That can be calculated using the extensions laid out below in Section IV, but is beyond the scope of this paper. However, the relative shifts in default probability over time are illustrative.

As is clear from Figure 7, the default probability associated with a given rating is surprisingly low. The overall risk of the Chilean banks in our sample peaked around the time of the 1998 crisis, and did not approach that level during more recent periods of financial volatility, such

[3] As we see below, this leveling-off has occurred at a very low level of risk.

as those preceding the 2002 Brazilian election, or associated with the 2005 unrest in emerging markets.

Figure 7. Risk-Neutral Probability of Default for Aggregated Banks



Additionally, Figure 7 presents the default probabilities not only for the aggregation of the banking system into one large bank, as in Figure 6, but also the asset-weighted average of the various banks' default probabilities. This measure shows slightly higher risks during crisis periods as relatively small banks, which are lost in the portfolio aggregation of the "big bank" measure, have a larger impact on a default-probability weighted average. This asset-weighted average thus indicates better whether an individual bank might run into risks, while the "big bank" aggregation shows a broader system-wide concern. The difference between the two is a rough indicator of the size of the banks most affected.

Moody's KMV estimates actual default probabilities by using historical default information which are "bucketed" and compared to modified CCA risk indicators. MKMV then estimates the risk-neutral default probability of default using the market price of risk technique which is described in the Annex. Such an extension of CCA-derived indicators is beyond the scope of this paper, but the magnitude of the default probabilities is illustrative: a rating of AAA is consistent under the Moody's methodology with a rating of around only 0.01 percent, while a Ba1 rating is associated with a default risk close to 0.13 percent. By the time an empirical default probability reaches 1 percent, the rating is generally in the Ca range.

Turning to individual banks, Figure 8 shows, for each of four dates in our sample, the percentage of banking sector assets (held by banks in our sample) with default probabilities at or below a given level. The closer the line for a given date is to the Y-axis, the higher the share of banking-sector assets held by banks associated with a given probability of default, and thus the safer the banking system. For the first date in our sample, September 10 1998, during the LTCM crisis, only around 20 percent of banking sector assets were held by banks which default probability was below 0.12 percent, and 15 percent of assets were held by banks with default probabilities greater than or equal to 0.3 percent.

Figure 8. Default Probabilities Relative to Asset Size for Chilean Banks

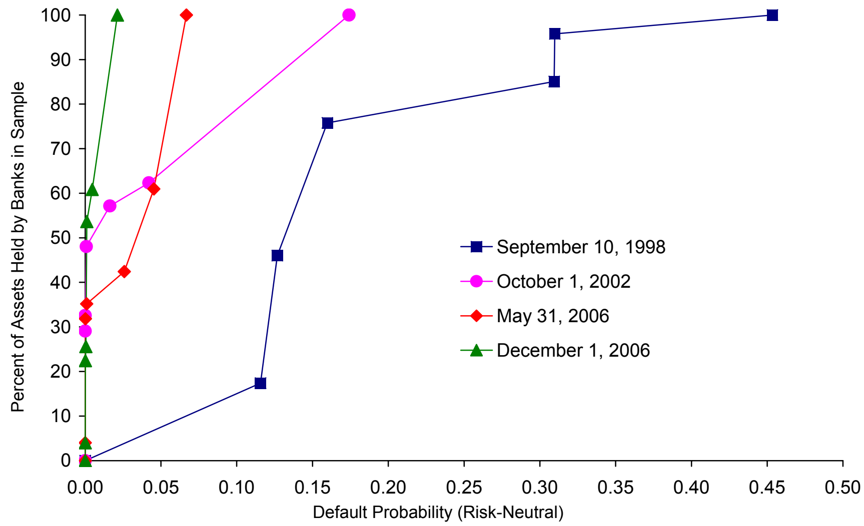


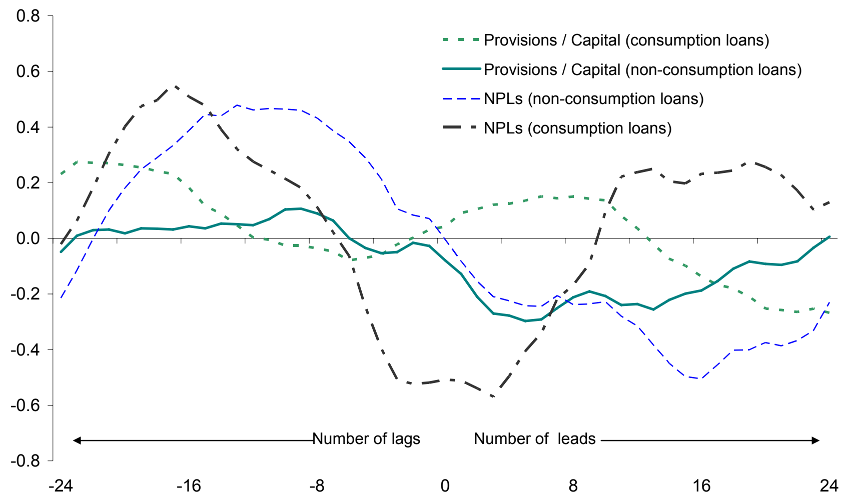
Figure 8 shows snapshots of how banking sector risk has evolved in Chile over time. During the height of the 1998 crisis, a fairly large of the assets held by Chile's main banks were held by banks with default probabilities greater than 10 percent, and that only a small share (less than 20 percent) was held by banks with default probabilities at very high levels exceeding 30 percent.

Over time as the health of the banking system has improved, these risks have fallen. Interestingly, the period just before the 2002 Brazilian presidential elections in late 2006 is associated with generally lower risks of default than the May 2006 "mini-crisis", which appears to have affected more Chilean banks, even though no banks show the more extreme values observed here for late 2002.

Correlations with other measures of banking risk

Risk measures derived from CCA have also been shown to be significantly correlated with other measures of banking risk. Figure 9 below, taken from Luna and Gómez (2007) presents the correlations between various measures of systemwide bank risk and the leads and lags of system DTD. For example, the measure of nonperforming loans (NPLs) for consumption purposes used in the paper are strongly correlated with declining distance to distress estimates from a few months previous; that is falling DTD predicts rising NPLs a few months later..,

Figure 9. Correlations between Banking Sector Risk Measures
and Leads and Lags of Systemwide Distance to Default



Source: Luna and Gómez, 2007

III. Relating Default Risk to Macroeconomic Variables

A. Motivation

Monitoring the risk of default of financial institutions is an important task for policymakers, and estimating the effect of forecast changes in the macroeconomic environment can provide useful insights, as can estimating the impact of shocks to macroeconomic or financial variables.

There is a wide range of variables that observers might reasonably expect to be correlated with banking sector risk. We focus on those variables with data available at a monthly frequency, and, to keep the dimensionality of the regressions down, on variables with relatively low correlation.[4] While full orthogonality can not, obviously, be assured, we tried to focus on relatively independent variables.

The variables chosen are presented in Table 1. These variables cover domestic developments (unemployment, CPI, and the IMACEC index of economic activity), foreign spillovers (U.S. interest rates and CPI), and financial-market developments (the VIX volatility measure, returns on the S&P 500 and the Chilean blue-chip IPSA index.) In each case monthly log returns are used in the VARs below.[5]

[4] All financial and macroeconomic data used in this section were obtained from the Haver economic database.

[5] For interest rates, the level and the change are used rather than log returns.

Table 1. Variables Used in Analysis

Variable	Chile	United States	International
Financial Variables			
Stock market returns	IPSA	S&P 500	
Volatility measure		VIX	
Prices	CPI	CPI	
Interest Rates	1/	1-Year Treasury Bill *(Level and Change)* 10-Year Treasury Bond *(Level and Change)* Difference (Yield Curve)	
Exchange Rates			Peso / USD Peso / BRA *real*
Real Variables	IMACEC 2/ Unemployment		Oil price Copper price

1/ Domestic interest rate is incorporated into CCA modeling.
2/ IMACEC is a monthly index of economic activity highly correlated to GDP growth.

Macro variables and asset returns

Due to banking heterogeneity, no small sample of variables appears to be sufficient to explain the variation in bank-asset returns across all the banks. As a diagnostic we run stepwise regressions for the asset returns of each of the banks in our sample against the full sample of macroeconomic variables. Each step of the stepwise regression process eliminates the variable with the last significance, until all remaining variables are significant at a specified level. Choosing the 5 percent level of significance, the variables laid out on Table 2 below are those with are jointly significant.

While some variables, such as the returns on the S&P 500, the level of U.S. short-term rates, and the slope of the U.S. yield curve, are significant for four of the seven banks, only one variables (the IMACEC) is significant in six. The stepwise regressions produce models with r-squared statistics in the 40–60 percent range, while smaller models using only those variables that are significant in at least three regressions (returns on the IPSA and S&P, the U.S. yield curve slope and one-year rate, and the IMACEC) produce adjusted r-squared statistics only in the 20–40 percent range. This is not a particularly bad result, but clearly significant information on the results of each bank is also available using a more tailored set of variables.[6]

To reduce the dimensionality of the state space—and also simplify the estimations below and produce impulse response functions which are easier to interpret—we apply principal component analysis to these variables.

[6] Also, these variables exhibit some cross-correlation. The principal component analysis discussed below results in uncorrelated factors which make analysis and estimation easier.

Table 2. Results of Stepwise Regressions

Variable (t-statistics in parentheses)	Returns on Implied Bank Assets						
	Bank 1	Bank 2	Bank 3	Bank 4	Bank 5	Bank 6	Bank 7
CLP-BRL Exchange Rate	-0.10		-0.35				
	-(2.43)		-(3.85)				
U.S. CPI	2.78		-10.14				
	(2.72)		-(3.65)				
IPSA Return	0.24		0.22			0.19	
	(6.67)		(2.15)			(3.15)	
U.S. Yield Curve Slope	0.01	0.09	-0.06	0.22			0.03
	(2.76)	(6.66)	-(2.29)	(4.17)			(2.58)
S&P 500 Return		0.25	-1.09	-8.14		0.47	
		(3.60)	-(6.39)	-(4.69)		(4.27)	
IMACEC		1.05	1.56	-20.90	2.16	1.92	0.93
		(3.33)	(2.30)	-(4.12)	(8.00)	(5.43)	(3.14)
U.S. 1-Year T-Bill Rate (Level)		0.06	-0.04			-0.01	0.02
		(6.18)	-(2.12)			-(2.38)	(2.37)
Oil Price			0.35			0.20	
			(4.72)			(5.33)	
Copper Price				1.28			
				(2.92)			
VIX				-1.36		0.13	
				-(3.27)		(3.47)	
CLP-USD Exchange Rate					-0.19		
					-(2.79)		
U.S. 1-Year T-Bill Rate (Change)						-0.16	
						-(5.68)	
Constant	0.01	-0.29	0.37	0.22	0.04	0.04	-0.13
	(0.33)	-(5.50)	(3.36)	(1.60)	(5.92)	(2.51)	-(2.52)
Adj. R-squared	0.38	0.42	0.50	0.42	0.41	0.53	0.13
F-statistic	16.09	18.69	13.30	6.68	35.16	16.62	5.84

B. Scenario Testing Using Principal Component Analysis

Principal component analysis

Principal component analysis (PCA) can be used to extract useful common information from a number of time series and synthesize it into a smaller number of factors. In our case, we are interested in distilling the information contained in our macroeconomic variables into a more manageable dataset which we can then use for analysis.

We apply PCA to the system of 15 macro variables. The procedure outputs 15 orthogonal factors, each of which is a linear combination of each of the macro variables, but of which the first four account for 70 percent of the variation of all the underlying macro variables.[7]

We apply a varimax rotation procedure to these four factors, a transformation which chooses factor loadings to maximize the largest of them and minimize the smallest. This procedure does not change the orthogonality of the factors, but by setting the factor loadings as close to

[7] These are the four factors with eigenvalues greater than one.

either one or zero as possible, it allows us to interpret the factors as something akin to a sum of a small number of variables, rather than only a combination of 15 variables.

The factor loadings of the macro variables onto the four significant factors are presented in Table 3, with the high loadings for the macro variables in bold. We categorize each of the factors according to the variables it weighs most strongly following the rotation. Based on the macro variables each of the factors loads most strongly, we interpret factors 1–4 as representing developments in financial markets, U.S. interest rates, cyclical variables, and Chile- or Latin-American specific factors, respectively.

Table 3. Factor Loadings and Variable Interpretation 1/

	Factor1	Factor2	Factor3	Factor4
U.S. Yield Curve Slope	0.00	**-0.93**	-0.10	0.00
Vix	**-0.76**	0.28	0.07	-0.07
Imacec	-0.02	0.01	0.32	**0.58**
Unemployment	0.19	0.09	-0.06	**-0.86**
CPI Chile	-0.38	**0.73**	-0.14	0.08
Copper	0.34	-0.21	**0.64**	0.22
Oil	0.06	-0.10	**0.87**	-0.13
S&P 500	**0.86**	0.23	-0.12	-0.11
CPI U.S.A.	-0.16	0.23	**0.82**	0.14
U.S. 10-Yr Rate (Chg)	**0.73**	0.00	0.40	-0.05
U.S. 1-Yr Rate (Chg)	**0.51**	0.21	**0.61**	0.18
IPSA	**0.73**	-0.20	0.16	0.00
CLP-USD Rate	**-0.49**	0.30	-0.23	-0.25
CLP-BRL Rate	0.18	0.12	-0.06	**0.81**
U.S. 1-Yr Rate (Lvl)	0.09	**0.95**	0.02	-0.02
	Financials	Interest Rates	Cyclicals	Regional/Domestic

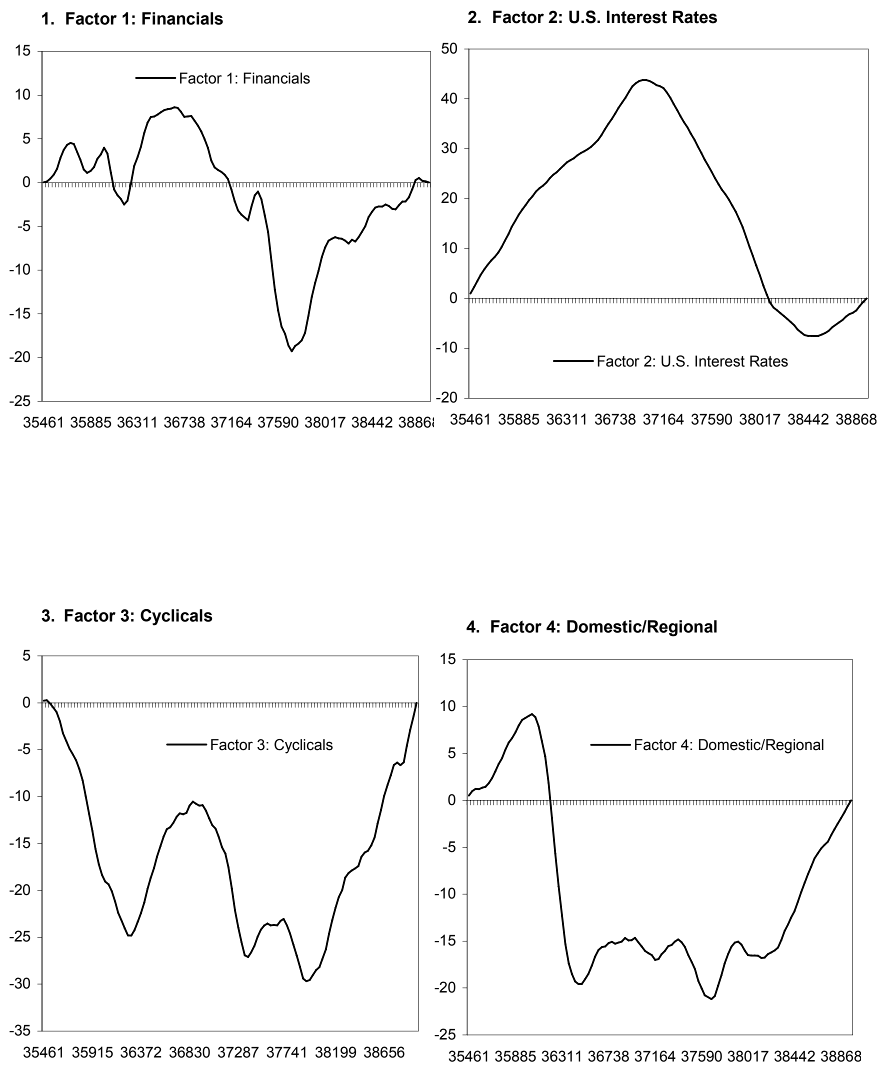
1/ Bold numbers indicate factors greater than 0.5 in magnitude

The factors themselves are shown in Figure 10. Factor 1, the “financials” factor, commoves very strongly with returns on the IPSA and S&P 500, which together have a correlation of -.6. The factor is negatively correlated both with the VIX volatility measure (the highest peak of the VIX in 1998 appears as the low point in the financials factor) and the peso-dollar exchange rate. Finally, changes in the U.S. 10-year Treasury bond rate, which also commoves with the S&P and the VIX, are linked to this factor.

The second factor shown in Figure 9, which we call the interest rate factor, mirrors the level of the U.S. 1-year Treasury bond rate and also (negatively) the slope of the U.S. yield curve. This factor rises from 1997 to 2000 as (short-term) interest rates rose in the U.S. and the yield curve correspondingly flattened, then reverses direction in 2000 as the yield curve slowly began to steepen again as short-term rates fell.

Most of the variation in the third factor comes from changes to oil and copper prices, and the U.S. CPI. There are also weaker loadings on the changes in U.S. interest rates and the Chilean IMACEC index. As copper, oil, and, generally, inflation tend to comove with the business cycle, we interpret this variable as representing cyclical factors in the world economy.

Figure 10. Significant Factors Output from PCA



Finally, the fourth factor weighs most strongly Chilean factors such as the IMACEC index and unemployment, but also the exchange rate with the Brazilian real. The graph of this factor in Figure 10 shows that its variation stems mostly from a large decline in 1998 and a subsequent recovery beginning in 2004. This tracks quite closely the evolution of most Chilean macro variables during the 1997-2006 period. However, the exchange rate between the peso and the *real* is not a domestic factor, and the 1998 crash was not unique to Chile. For this reason, we interpret this factor as a domestic/regional factor: many variables in Latin America, but very few elsewhere, exhibit this pattern.

As these four factors account for more than 70 percent of the variation in all 15 of the macroeconomic variables laid out above, the relationship between the risk measures derived above and our factors should be quite similar to their relationship with those macro variables surviving in the stepwise regressions above, but allow us to use a common model across all seven banks, rather make do with a small set of variables that are useful for the largest number of banks while neglecting other variables that might help with the results of only a few.

Vector autoregressions

We next estimate vector autoregressions (VARs) for the factors and the implied assets extracted above. We estimate one VAR for each bank, and each VAR includes five variables: the bank's implied assets and the four factors. The ordering of the system is to some extent trivial: while each of the factors may Granger-cause changes in the bank's implied assets, the factors cannot, by construction, contemporaneously affect each other, as they are orthogonal. However, they can be autocorrelated, and can Granger-cause changes in other factors.

Using asset returns rather than distance to default or expected default frequencies is not an obvious choice. The results of VARs run using D2D and EFDs are similar to those run using assets, but the fewer coefficients are significant. Since the risk measures are merely transformations of the asset data, no information is lost by using assets instead of risk measures, and we derive D2D measures below from simulated asset series.

The asset returns are all stationary under the Dickey-Fuller criterion at the 5 percent level of significance, as are the log changes in macro variables that we use. Each VAR is specified in two lags. Schwarz and Akaike information criteria were calculated for each bank at one, two, three and four lags. The results differed across banks, but the AIC and SIC criteria point to two lags more frequently than to any other number of lags.

In the VARs returns on the assets of each of the banks show some persistence: the first lag of the bank's assets is significantly positive in all regressions, and second lag is significant in two cases. This similarity breaks down when we look at factors, however. Each of the macroeconomic factors is significant for at least one of the banks, though the financials and domestic/regional factors are significant for four of the variables, while the interest-rate and cyclical factors are only significant for one of the banks.

Our sample can be divided into banks 1-3, which are the three largest private banks in the system, and banks 4-7, which are smaller. The first three banks cumulatively account for 52 percent of the assets of the financial system (or 59.9 percent of the nonstate financial system), while the last four account for 20.1 percent (23.2 percent of the nonstate system). The financials variable is significant for the first three, large, banks but not for the smaller ones, while the regional factor is significant for the smaller banks, but not for the larger ones.[8]

[8] All figures for bank assets and concentration are as of July 2007.

The reason for this is not clear. Both the larger banks and the smaller banks focus on corporations: 73 percent of the loan portfolio of the larger banks is to companies, while 67 percent of the small banks' portfolios are. It is possible that the larger banks focus on larger, more internationally connected companies such as exporters, while the smaller banks focus on smaller corporations with fewer links to financial markets, but without company-level data on bank lending, this cannot be verified.

An improvement in financial conditions (that is, a decline in the VIX, or a rise in the IPSA or S&P) is tied to significantly higher asset returns at two of the three largest banks and one of the smaller ones, but lower returns at one of the larger banks. This is somewhat counterintuitive: it seems unlikely that a bank can focus its lending portfolio on countercyclical companies. The signs of the coefficients on the regional factor are more intuitive: in each case where the variable is significant, and three of the five where it is not, an improvement in Chilean domestic conditions (such as a decline in unemployment, an improvement in IMACEC, or a depreciation of the peso relative to the Brazilian *real*) leads to an increase in the assets of the banks.

The interest-rate and cyclical factors are less significant in our regressions. Our stepwise regressions above also showed that cyclical variables such as copper and oil prices were related to banking-sector risk at least for some banks, and that at least one cyclical variable could explain a significant share of variation in banking-sector implied assets for six of the seven banks. Interest-rate variables were even more useful, and significant contributors in four of stepwise regressions. However, once we distill macroeconomic developments into orthogonal factors and estimate a consistent model across the different banks, the picture changes slightly, and each is significant for only one bank.

In both cases this is counterintuitive. The effect of rising U.S. interest rates (and thus a flattening of the U.S. yield curve) on liquidity in Latin American financial markets is widely recognized, as is the impact of commodity prices and cyclical developments in the U.S.. In this case, however, it appears that the effect of interest rates and such cyclical variables are weaker than simultaneous innovations in other financial-market variables, and those are the coefficients that here have the most significance, with interest-rate and cyclical developments relegated to a secondary position.

Impulse response functions

From the VARs presented above, we derive impulse-response functions (IRFs) that we use to show how a shock to each of the above factors impacts the implied assets of each of the banks. IRFs created from the factors above have an advantage above IRFs calculated from traditional macro variables: we cannot separate the effect of a change in the VIX from a change in the S&P index, for example, but the factors derived from the PCA conducted above are by construction orthogonal; the impulse response to the financials factor shows the impact of a shock to that factor (itself a linear combination of macro variables) on the assets of each of the banks *keeping all the other factors constant.*

In interpreting these results, it should be borne in mind that each factor is merely a linear combination of the underlying macro variables, and while we talk about the impact of the interest-rate factor or the financials factor, this is only shorthand for a grouping of shocks that tend to affect a subset of the macro variables simultaneously, with minimal (if not necessarily zero) effect on other macro variables. That is, a jump in the VIX is correlated with negative returns to the IPSA and the S&P indices, which we interpret as a shock to the financials factor, even though not every shock to the VIX will have the same transmission to the IPSA and S&P, nor will it in real life be independent of the other macro variables.

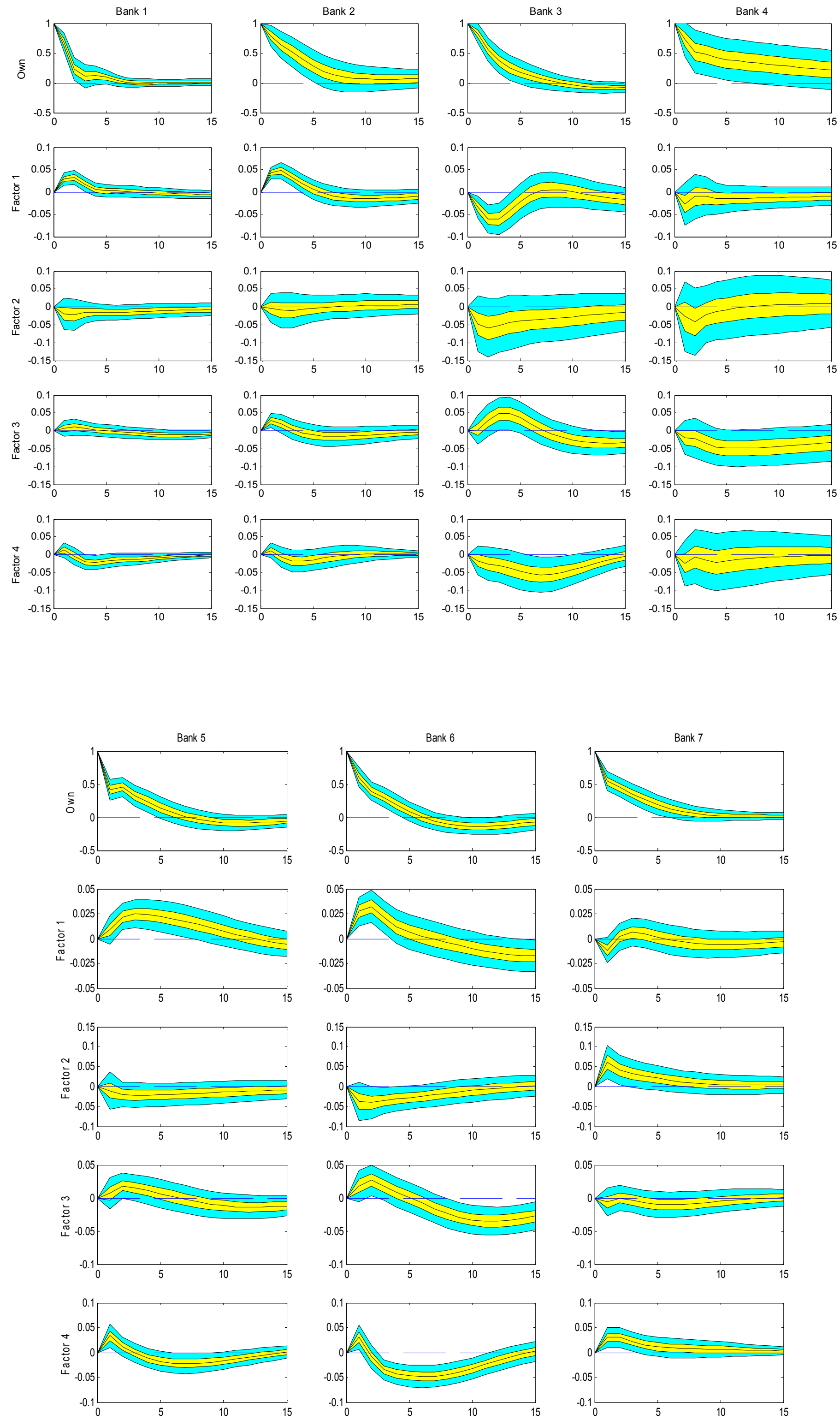
The impulse responses are graphed in Figure 11.The first set are each bank's response to a shock to a shock to its own asset level. The IRF thus measures the persistence of shocks to banks. As discussed above, these variables were highly significant in regressions, and the impulse responses are also quite large. In each case, a shock to the assets of a bank results in continued increase of assets for a few months, with half the shock dissipated within four months for all banks, and 90 percent of the shock dissipated within eight months for all the banks but one.

A shock to the financials factor causes a strongly positive impulse response for four of the banks but a negative one for another bank, with two close to zero. Presumably for the same reasons posited above, the implied assets of one of the banks in the sample declines as a result of a (positive) financial-markets shock, while for the other four banks, the intuitive result of an improvement in financial conditions.

The banks also differ in the timing of their response to the financials shock. Three of the four banks with the intuitively-signed response, as well as the bank showing a negative response, have a maximum response to the shock two to three months afterward. These are the same four banks for which the financials variable was significant in the VARs above. The final bank (number 5) shows a maximum response to the shock a few months later, and the shock is also more persistent. The VAR for this bank did not have a significant coefficient on the lags of the first factor, but did on the fourth factor. As there are nontrivial feedback loops between the factors, the impulse response from the fourth factor back to the first results in a delayed but significant impulse-response for this bank as well. In this case, financial shocks may not affect bank 5 as severely as others, but the feedback from a regional shock to the financials factor can be significant enough to cause a delayed response.

A shock to the interest-rate factor produces a significant impulse response only for the seventh bank, though here again the result is somewhat counterintuitive: a positive shock to the interest rate factor (associated with an increase in short-term U.S. interest rates or a flattening of the yield curve) results in an increase in the implied assets of bank 7, with the other banks showing the intuitive, if insignificant, opposite result.

Figure 11. Impulse Response Functions



(Bands indicate 50 and 95 percent confidence intervals)

The cyclicals factor displays a pattern similar to the interest-rate factor. The impulse response is significant for the two variables showing a significant coefficient in the VAR above, but not for the others. In both cases, the sign of the result is in the expected direction: an improvement in cyclical conditions (i.e., rises in oil or copper prices, increases in inflation or short-term rates) results in an increase in banks' implied assets which peaks after a few months and then, the factor itself being cyclical, turns negative. The banks with significant impulse responses in this case, numbers 2 and 5, are one of the large ones and one of the small ones. The other banks showing insignificant responses display a broadly similar pattern, with the exception of bank 4.

Finally, the domestic and regional factor provides significant responses for three of the banks. In this case, the impulse response is significant for the small banks, numbers 5 through 7, the same banks that showed significant coefficients in the VARs. In each of these cases, as well as in two of the less significant ones, the impulse responses are of the expected sign. For two of the banks, the shocks are not persistent: within six months the effect of a positive shock to the local economy has dissipated. For the final bank, bank 7, the effect is more persistent, with half the effect dissipated within six months.

The impulse responses thus reflect the results shown in the VARs above. Each of the banks responds quite strongly to either the domestic/regional or the financial factors, while the responses to changes in the interest rate or cyclical factors have a significant impact on only one bank each. In general, the larger banks are more responsive to developments in financial markets, while the smaller banks respond more strongly to developments in the domestic economy. In both cases, shocks are relatively short-lived, but for some banks can be more persistent than for others.

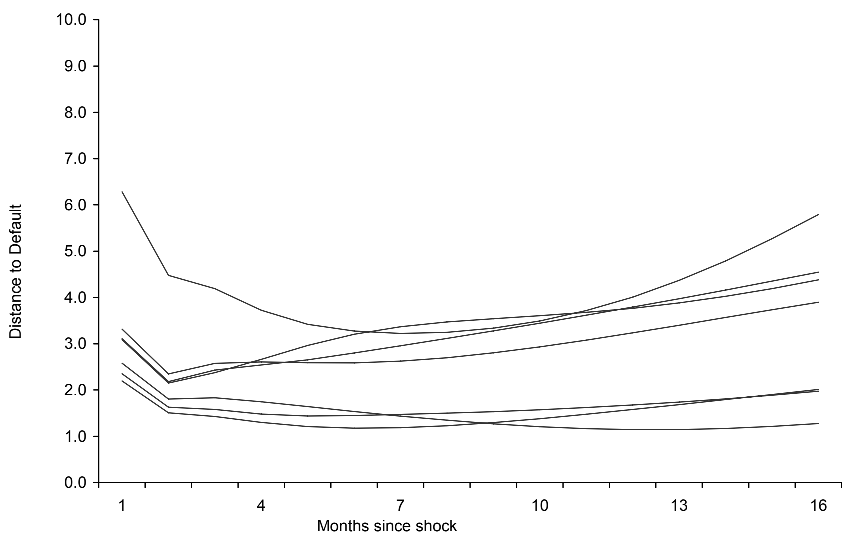
Scenario testing

Deriving impulse responses allows us to extend this analysis further by testing scenarios. Below we derive CCA risk measures under scenarios calibrated to approximate recent shocks affecting Chile, to estimate the impact such a shock would have on banking-sector risk today.

For each scenario we estimate the distance to default (D2D) of each of the banks under the given scenario. As above, the impulse responses consistently and significantly different from zero are graphed in black, while the others are shown in gray. Each series represents the simulated D2D following a shock to the cited variable. The D2D formula requires as inputs assets, asset volatility, as well as the parameters indicated above. We derive assets from our impulse responses, with the initial value based on the values observed for the end of our sample in February 2007. The parameters we use are the constant ones used above for the derivation of the historic risk measures. For asset volatility, we use the final observed value. As each of the cases below represents a shock to economic conditions, we might expect that asset volatility, which is closely related to equity volatility, would rise. A higher asset volatility in all cases implies a lower D2D, thus the scenarios laid out below likely overestimate the actual D2D observed. Some alternatives are presented below as robustness tests.

The scenario presented in Figure 12 is intended to be similar to the financial conditions at the beginning of the Russia/LTCM crisis in late 1998. At that time, the VIX jumped by about two standard deviations, while stock markets around the world, including in the U.S. and Chile, fell dramatically. Multiplying the log changes in those variables by the factor loadings derived above gives an average innovation to the financial factor slightly less than one.

Figure 12. Scenario 1: Shock to Financials Factor Comparable to 1998

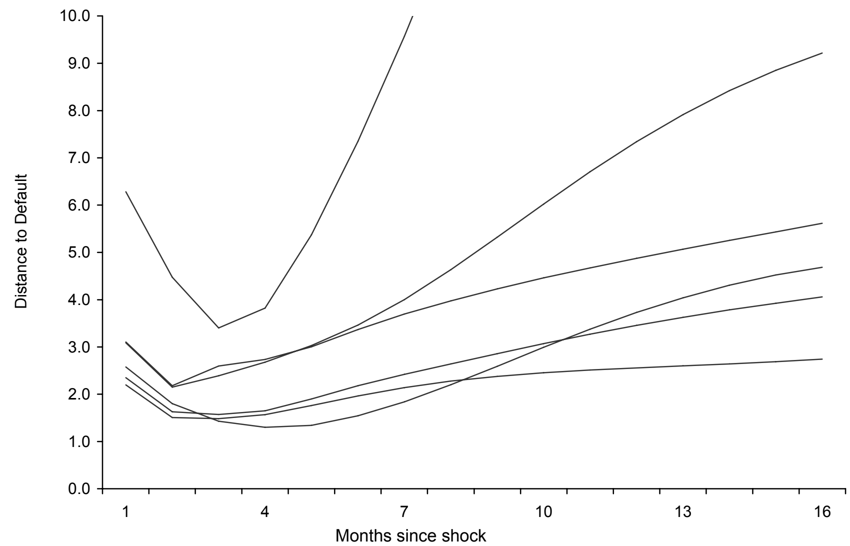


For each of the banks, distance to distress falls in the months immediately following the shock. As D2D measures the number of standard deviations of implied assets between the bank's current position and its default barrier, a decline of one in D2D represents a statistically significant increase in the probability of a bank's asset level falling beneath the default barrier. If we apply a slightly more rigorous standard such as distance to distress (a level below which the government would intervene and bail out the bank) this amount would be even lower, depending on the threshold for government intervention.

Four of the five banks show recoveries beginning a few months after the shock. In two cases, the recovery is rapid, and within 10 months the banks' assets have risen above the original level. In the other cases, the recovery from financial turmoil is slower. In both cases, one of the two banks is one of the large ones, and the other is a smaller bank. To a regulator, this different pace of recovery should imply that while some banks have historically been able to bounce back quickly following a crisis, others have taken a longer time to recover, and should be monitored more closely during the aftermath. The most extreme case we observe here is of the fifth bank, which does not begin to revert until a year after the shock, showing that some Chilean banks (here one of the smaller ones) may take a long time to bounce back from episodes of financial turmoil.

In the second scenario (Figure 13), we look at the response of the variables to a domestic shock. We calibrate the shock to be comparable to the increase in unemployment observed during 1999 as Chile began a long period of adjustment following the 1998 financial crisis. Here, as in the first scenario, there is a decline in D2D following the shock of between one and two standard deviations (except for one outlying bank with idiosyncratic results). This shock is less persistent than the financials shock, however, and recovery in all cases begins after a period of less than six months.

Figure 13. Scenario 2: Shock to Domestic Factor



There is some heterogeneity: one of the banks' implied assets bottoms out a few months later than the others, but then recovers more quickly. But overall a single domestic shock appears to have less of a long-run impact than the financials factor. While it is true that financial turmoil generally lasts less time than a recession, shocks of the magnitude we use in both of these scenarios are not common. A domestic factor shock of this magnitude only hit Chile during the 1999 crisis; the subsequent recession was marked more by a stagnation in employment and the IMACEC than by continued large increases in unemployment or shrinking of production. Thus the short time period (one month) of each of these shocks does not distort the effect of their impact.

C. Robustness Tests

Volatility and interest rates

As discussed above, two areas where the parameterization of the model differs from reality are in the selection of the riskfree interest rate incorporated into the model and the estimation of volatility. The results presented in Section 2A above show that using another widely used volatility measure would not have much impact on results. Allowing for a variable interest rate raises the question of which interest rate might most accurately be used, a nontrivial question. The impact on results, however, is too small to be highly significant during those periods (low-risk) in which small changes are important, and large only during those periods (high-risk) in which resulting probabilities will be very high under any assumption.

Estimation period

Clearly much of our analysis is affected by the financial turmoil of 1998. To see how much of the analysis is dependent on this unusual period, we reestimate both the stepwise regressions, the principal component analysis and the VARs dropping all 1998 observations.

The stepwise regressions, intended to show which of the macro variables used in our sample have the greatest explanatory power for each of the banks' asset returns, are not substantively changed. In each case, dropping the 1998 observations does not change the variables that survive the stepwise procedure, and does not materially change the estimates of the parameters.

Beyond this naïve point, the principal component analysis, while largely unchanged, does have one significant difference. Following the rotation of the covariance matrix, four factors accounting for 70 percent of the macro variables' variance had eigenvalues greater than one; these were the variables we preserved for the VARs. Dropping 1998 increases the explanatory power of the first four factors, which now account for 73 percent of overall variance, but a fifth factor has an eigenvalue greater than one. Applying our selection criterion above, we would also include this factor in the regressions.

The interpretation of the factors is largely unchanged. Each of the first four factors weighs most the macro variables in a similar fashion to the analysis above, but the fifth factor most heavily weighs the U.S. exchange rate, copper prices, and changes to U.S. interest rates. Thus while the qualitative interpretation of the first four factors is essentially unchanged, the fifth factor is difficult to place.

Despite including five factors in the VARs, the results are not dramatically different from the four-factor VARs laid out above. The first, financial developments, factor is significant for the same banks (the large ones and number 6) while the fourth, domestic factor, is significant for the smaller banks. The new factor is significant for two banks, comparable to the interest-rate and cyclical factors above.

Overall these results are sufficiently similar to the main results that it does not appear that the 1998 observations are substantively changing our results. Including them thus does not appear to be unwarranted. In fact, these observations, as they represent the largest-scale financial crisis in our estimation period, are likely to overestimate the riskiness of banks, which for our purposes, is not a major drawback.

IV. Areas for Further Research

A. Modeling Bank Risk with CCA

Extensions of current analysis

The analysis in this paper models banks individually, and does not allow feedback between banks. This restriction may be justified in a case in which interbank lending is quite small, banks are highly competitive, and banks are quite heterogeneous. These assumptions may not be met in every case however, and estimation of a broader VAR allowing feedback effects from, for example, larger banks to smaller ones, might improve the fit. The data in this paper extend back only to 1998, unfortunately, and increasing the number of parameters through estimation of such a high-dimensionality VAR would be problematic.

The constant interest rate assumption in this paper is also unrealistic, though as laid out above, the resulting distortion of results should be minor. Using a series of risk free interest rates would improve the realism of the estimation. The Merton Model has been extended to include stochastic interest rates as well. Shimko, Tejima, and Van Deventer (1993) include a Vasicek interest rate term structure model which relaxes assumption (iii) above allowing the risk free interest rate to change and including the correlation of asset return with the interest rate. There are two stochastic factors, the asset and the interest rate and this model is frequently called the STV model. This closed form model is a very useful extension by including the impact of changing interest rate term structures. This allows not only for a realistic interest-rate series, but also in a case such as the one in this paper would allow scenario testing with varying assumptions or calibrations for how macroeconomic shocks affect both short- and long-term rates.

Additionally, the Black-Scholes-Merton assumption of normally distributed asset returns is highly unrealistic for financial assets. The widely recognized skewness of financial sector returns, which large drops far more likely than the normal distribution would predict, reduces the usefulness of the normal model. This lack of realism can be addressed, however, by modifying the formulas underlying the CCA. One method used is rather than calibrating returns to a normal distribution to calibrate them to a combination of two (or more) lognormals, which allows both for the nonzero skew exhibited by financial returns and also for a higher kurtosis than assumed under basic option pricing formulas. Another, related way to model fat-tails or skewed asset distribution is the by having the asset volatility vary with the level of the asset. This is the constant elasticity of variance approach. Market data determines how the volatility changes as the asset varies.

Some of the results presented above are puzzling, and call for a more detailed analysis of the banks in the sample. The result that improvements in financial-market conditions affect most banks positive but affect one of the main Chilean banks adversely is quite counterintuitive. The differences between small and large banks are also striking, specifically, the difference in responses to domestic and financial-market developments. A more detailed analysis of the lending portfolios of the banks might shed light on these differences and would provide more detailed insights into which banks might be most exposed to various shocks.

Stress-testing and assessing capital adequacy using CCA models

One major goal of financial sector stress-testing is to assess capital adequacy of various institutions under different potential shocks. Shocks to financial institution assets and asset volatility and/or interest rates and other parameters can be used in the CCA model to measure the impact on capital adequacy. An advantage of using CCA models for financial institutions is that the capital adequacy can be related to asset level, asset volatility, and default probability on the institution's liabilities and other factors. This way to calculate capital adequacy has been extended to include interest rates, interest rate volatility and correlation of asset return with interest rates by van Deventer and Imai (1997, and 2003) and Belmont (2004) using the Merton-STV model.

The financial stress testing process commonly used by central banks and banking supervisors use various models to measure the change in expected default probability of the obligors, usually representative corporates or corporate sub-sectors. The default probabilities are then used with estimates of exposure and loss given default in a model of bank credit losses (e.g. Credit Risk Plus) to estimate the impact on economic capital.[9] Calibrated CCA models of financial institutions can be used to estimate capital adequacy without the need for detailed data on default probabilities or loss given default of obligors. As pointed out by van Deventer, "In the capital allocation [using the Merton-STV model], note that we didn't use the probability of default or the loss given default in allocating capital. *We don't need to*, because the probability of default and loss given default are both implied by the STV model and the value of asset volatility and interest rate and correlation." This makes CCA a potentially useful tool when detailed data on obligor exposures, default probabilities, or loss-given-default is not available.

B. Incorporating CCA into Macroeconomic Models

Embedding CCA risk measures in broader macroeconomic models

Since the economy and interest rates affect financial sector credit risk, and the financial sector affects the economy, an important issue is whether credit risk indicators should be included in monetary policy models and, if so, how. Including an aggregate credit risk indicator (CRI) in the GDP gap equation and testing whether or not the coefficient is and important first step to get a better understanding of how the financial sector credit risk affects GDP. The next step could be to add a fifth equation relating the CRIs to GDP and interest

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[9] See Sorge (2004). Work at the ECB by Castren et. al. (2007) uses MKMV median default probability for various corporate sectors with a VAR or Global VAR. Also see Pesaran et. al. (2004) and Alves (2005).

rates (this could draw on analysis from the previous section relating financial risk indicators to macroeconomic variables).

Using past data, it might be interesting to include the CRI in the policy rate reaction function to examine whether financial stability appears to have been taken into account when setting interest rates in the past. A variation of this approach is being investigated in research department of the Central Bank of Chile.[10] The approach taken in the Central Bank of Chile is to first estimate the distance-to-distress for the banking system (each individual bank's distance-to-distress from a CCA model is weighted by bank implied assets). The distance-to-distress for the banking system is included in the GDP gap equation and in the policy rate reaction function. The model parameters are then estimated using historical data, including the distance-to-distress indicator. The approach can be used to examine the tradeoffs between GDP, inflation, and distance-to-distress for the banking system.[11]

V. Conclusion

Contingent claims analysis can be a useful tool for assessing the risk of financial companies. No risk measure is perfect, and CCA has both advantages and disadvantages. For example, by being based on market data, the CCA cumulates the information of market participants in a forward-looking way that other measures of bank risk do not do. But markets themselves do not always foresee risky events, and the CCA also faces this limitation.

In the case of Chile, CCA risk measures show the gradual improvement in the health of Chilean banks over the past decade while also clearly indicating those periods when risk rose due to international shocks. The measures derived in this paper are correlated both with other measures of bank risk (in some cases leading them) as well as with macroeconomic and financial-market variables.

The inclusion of these risk measures in a VAR with macroeconomic variables is the chief achievement of this paper. Chilean banks differ drastically in their short- and medium-term reaction to various macroeconomic shocks, both domestic and international. This makes it difficult to arrive at a parsimonious model of economic shocks that can be applied across banks. This paper takes a wide variety of Chilean and international variables and distills the large majority of their variation into four macro factors, which are then used to assess the interaction between bank risk and these broader macro variables. We interpret these factors

[10] Restrepo, Luna, and Gray (draft).

[11] A related issue is whether an indicator of market risk appetite such as the VIX should be included in monetary policy models along with the credit risk indicator. This could help estimate the impact of the credit risk indicator on the GDP gap, adjusted for changes in risk appetite.

as representing developments in financial markets, U.S. interest rates, cyclical variables, and Latin American or Chilean-specific factors.

The VAR results show that innovations in these factors are quite strongly tied to the evolution of bank risk. Each of the factors is significant in at least one of the VARs, and some are significant for most of the banks. Impulse response functions derived from the VARs show a wide variety of significant effects, as well. We find that developments in financial markets are most significant in explaining the variation in banks' risk during our sample, with positive developments in financial markets being strongly related to a reduction in the risk assessment of most of the banks. Interest rate changes in the United States (the second factor) are less strongly tied to the riskiness of Chilean banks. The riskiness of most of the banks moves procyclically, at least as measured by relation to the cyclical factor, which is intuitive. However, some banks do not react strongly to this factor at all. Finally, the regional/domestic factor appears to have a much stronger effect on the smaller than on the larger banks. This is in opposition to the result that the financials factor appears to be more strongly tied to changes among the larger banks.

Based on these results, it would appear that in assessing the importance of various shocks to banking sector risk in Chile, regulators should focus their attention on larger, more internationally connected banks in assessing the possible impact of financial-market shocks, and alternately on smaller banks in assessing the risk of regional or domestic shocks. At least when isolated from other events, U.S. interest rates themselves do not appear to strongly impact banking-sector risk, and the evolution of cyclical variables, while affecting most banks intuitively, appears to effect some banks more strongly than others, and indeed, one bank appears to be almost countercyclical.

Another crucial difference among banks is the persistence of shocks. In some cases, the increase in risk associated with an innovation in one of the factors dissipates relatively quickly, and the bank returns to its baseline level of risk in a few months. In some cases, however, the reaction of one or a few of the banks begins later and lasts longer than in case of the other banks. In assessing the effect of a world shock on the Chilean banking system, this difference in reaction times should be taken into mind: the damage caused to most banks is not immediate, but can take a few months to appear. Moreover, the time lag varies among banks, and as some banks are emerging from the shock, the risk associated with others might still be rising.

Numerous extensions to this analysis can be envisioned. Monetary and macroeconomic models can attain greater realism by explicitly including measures of financial risk, and CCA provides an easily calculated option for this. More broadly, the realism of macroeconomic analysis can be greatly increased by incorporating risk assessment tools from finance, and CCA can be a building block in this work as well.

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Annex 1. Framework for Contingent Claims Analysis, Risk Measures, and Spreads Using Black-Scholes-Merton Formula

The total market value of assets at any time, *t*, is equal to the market value of the claims on the assets, equity and risky debt maturing at time *T*:

Assets = Equity + Risky Debt

$$A(t) = J(t) + D(t)$$

Asset value is stochastic and in the future may decline below the point where debt payments on scheduled dates cannot be made. The equity can be modeled and calculated as an implicit call option on the assets, with an exercise price equal to the promised payments, *B*, maturing in *T-t* periods. The risky debt is equivalent in value to default-free debt minus a guarantee against default. This guarantee can be calculated as the value of a put on the assets with an exercise price equal to *B*.

Risky Debt = Default-Free Debt − Debt Guarantee

$$D(t) = Be^{-r(T-t)} - P(t)$$

We omit the time subscript at t = 0. We will define $\overline{B} = Be^{-rT}$.

The value of the equity is computed using the Black-Scholes-Merton formula for the value of a call:

$$J = AN(d_1) - \overline{B}N(d_2)$$

The value of the put option is computed with the formula:

$$P = \overline{B}N(-d_2) - AN(-d_1)$$

Where,

$$d_1 = \frac{\ln\left(\frac{A}{B}\right) + \left(r + \frac{\sigma^2}{2}\right)T}{\sigma\sqrt{T}}$$

$$d_2 = d_1 - \sigma\sqrt{T}$$

r is the risk-free rate

σ is the asset return volatility

$N(d)$ is the cumulative probability of the standard normal density function below d.

The “risk-neutral” or “risk-adjusted” default probability is $N(-d_2)$.

The formula for the "delta" of the put option is $N(d_1)-1$.

The distance-to-distress is d_2, the number of standard deviations of asset volatility from the promised payments.

The yield to maturity on the risky debt, y, is defined by:

$$D = Be^{-yT}$$

$$y = \frac{\ln(B/D)}{T}$$

And the credit spread is thus $s = y - r$

Example: Assuming that: A = \$100,

σ = 0.40 (40%)

B = \$75

r = 0.05(5%)

T = 1 (one year)

The value of the equity is \$32.367, the value of risky debt is \$67.633; the yield to maturity on the risky debt is 10.34%, and the credit spread 5.34%. The risk adjusted probability of default is 26%.

Calculating Implied Assets and Implied Asset Volatility

The value of assets is unobservable, but it can be implied using CCA.

In the Merton Model for firms, banks and non-bank financials with traded equity the following two equations are used to solve for the two unknowns A, asset value, and σ_A, asset volatility. (See Crouhy, Mark and Galai).

$$J = A_0 \mathrm{N}(d_1) - \overline{B}\mathrm{N}(d_2)$$

$$J\sigma_J = A\sigma_A N(d_1)$$

Market Price of Risk (how to go from actual world to RN world valuation)

Thus, there are two types of distance-to-distress, d_2 with an asset drift of the risk-free rate, and $d_{2,\mu}$ with an asset drift of μ_A. There are two corresponding types of default probabilities, $N(-d_2)$ is the risk-adjusted or risk-neutral default probability and $N(d_{2,\mu})$ is the "actual" default probability. $N(-d_{2,\mu}) = N(-d_2 - \lambda\sqrt{t})$. Market price of risk reflects a certain degree of risk aversion and can be measured in several different ways. It can be see that

$d_{2,\mu} - d_2 = \dfrac{\mu_A - r_f}{\sigma_A}\sqrt{t} = \lambda\sqrt{t}$, where λ is the market price of risk.One can calculate the market price of risk from the capital asset pricing model. $\lambda = \rho_{A,M} SR$ which means the market price of risk can be estimated as the correlation of the asset return with the market and Sharpe Ratio for the market.

This can be derived as follows. CAPM states that the excess return of a security is equal to the beta β of the security times the market risk premium $(\mu_M - r)$.

$$\mu - r = \beta(\mu_M - r)$$

Beta is equal to the correlation of the asset with the market times the volatility of the asset divided by the volatility of the market.

$$\beta = \frac{\operatorname{cov}(r_V, r_M)}{\operatorname{var}(r_M)} = \rho_{A,M}\frac{\sigma}{\sigma_M} \qquad \text{So,} \qquad \mu - r = \rho_{A,M}\sigma\frac{(\mu_M - r)}{\sigma_M} = \rho_{A,M}\sigma SR$$

Here SR is the Sharpe Ratio for the market, and

$\dfrac{\mu - r}{\sigma} = \rho_{A,M} SR$ and $\dfrac{\mu - r}{\sigma} = \lambda$, so $\lambda = \rho_{A,M} SR$

Extensions of the Merton Model

Numerous extensions of the original Merton Model have been developed that relax certain assumptions in the original model. Restrictions of the model include the assumptions that: (i) default can occur only at the maturity date of the debt; (ii) there is a fixed default barrier; (iii) there is a constant risk-free rate; and, (iv) asset volatility is constant. Cossin and Pirotte (2001) and Jain (2005) provide a good summary of extensions of the Merton Model.

Black and Cox (1976) extended the Merton Model to relax the assumptions (i) and (ii) above by introducing a "first passage time" model where default can occur prior to the maturity of the debt if the asset falls below a specified barrier function for the first time.

Although the strict theoretical condition in the Merton Model for default is that the value of assets is less than the required payments due on the debt, in the real world, default typically occurs at much higher asset values, either because of a material breach of a debt covenant or because assets cannot be sold to meet the payments ("inadequate liquidity") or because the sovereign decides to default and induce a debt renegotiation rather than sell assets. To capture these real-world conditions for default in the model, we specify a market value of total assets at which default occurs. We call this level of assets that trigger default the "distress barrier." This barrier can be viewed as the present value of the promised payments discounted at the risk-free rate. The approach used in the KMV model sets the barrier level equal to the sum of the book value of short-term debt, promised interest payments for the next 12 months, and half of long-term debt (see Crouhy, et. al. (2000), Saunders and Allen (2002) and KMV (1999, 2001)).

In the 1990s the model was called the VK model (Vasicek and Kealhofer) and it has multiple layers of liabilities and several confidential features. MKMV's EDF credit measure is calculated using an iterative procedure to solve for the asset volatility. This distance-to-distress was then mapped to actual default probabilities, called CEDFs (cumulative expected default probabilities), using a database of detailed real world default probabilities for many firms. The MKMV distance-to-distress and the CEDF are calculated as follows:

$$DD_{KMV} = f\left(\frac{\ln\left(A_0 / B_t\right) + \left(\mu_A - \sigma_A^2 / 2\right) t}{\sigma_A \sqrt{t}}\right)$$

$$CEDF_t = f\left(DD_{KMV}(t)\right)$$

Note that this definition of DD_{KMV} includes the real drift of the asset, μ_A. whereas the distance-to-distress from the Merton approach has *r* for the asset drift. Since MKMV estimates the actual default probabilities, the risk neutral default probabilities are calculated from the correlation of the implied asset with the market, the market Sharpe Ratio, and time. (See Crouhy et. al. (2000) and MKMV 2001).

The original CreditGrades model (2002) included a diffusion of a firm's assets and a first passage time default with a stochastic default barrier. The model was modified to incorporate equity derivatives (Stamicar and Finger 2005). Recent research has studied the relationship between the volatility skew implied by equity options and CDS spreads (Hull et. al. 2003). They establish a relationship between implied volatility of two equity options, leverage and asset volatility. This approach is, in fact, another new way of implementing Merton's model to get spreads and risk-neutral default probabilities directly from the implied volatility of equity options.

The Merton Model has been extended to include stochastic interest rates as well. Shimko, Tejima, and Van Deventer (1993) include a Vasicek interest rate term structure model which relaxes assumption (iii) above allowing the risk free interest rate to change and including the correlation of asset return with the interest rate. There are two stochastic factors, the asset and the interest rate and this model is frequently called the STV model. This closed form model is a very useful extension by including the impact of changing interest rate term structures. Longstaff and Schwartz (1995) take the Black and Cox model and add in stochastic interest rates, similar to the way STV includes interest rates.