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Kurt Jesswein
Editor
Sam Houston State University

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Kurt Jesswein
Sam Houston State University

ESTIMATING THE PROBABILITY OF A BANK RUN BY MONTE CARLO SIMULATION

Samih Antoine Azar, Haigazian University

ABSTRACT

A renowned theoretical model of a bank, due to Diamond and Dybvig (1983), and modified and simplified by Allen and Gale (2009), forms the basis of this paper's Monte Carlo simulations. The model compares the expected utilities when a bank run is avoided by the bank, and when it is a possibility with a set probability. The model has five unknown parameters. All of these are simulated except for the isoelastic utility function which is assumed to take five different risk aversion coefficients. Across utility functions, the mean probabilities of a bank run are estimated with high precision, and are found to be significantly different from each other. However these mean probabilities lie economically in a rather tight range between 3.50% and 5.41%. This range is reasonable and realistic, providing additional support for the underlying theory. Moreover a sensitivity analysis is undertaken to find out the effects of changes in the average productivity of the long asset and of changes in uncertainty. The results are according to expectations.

Keywords: *banks, bank run, probability of a bank run, Monte Carlo simulation, isoelastic utility function, risk aversion, uncertainty.*

JEL Classification Code: G2

INTRODUCTION

A research paper on banks needs to begin by asking and answering two main questions. Why do banks exist? And are banks flawed institutions? The first question has received a lot of attention. A quick list of the reasons for the existence of banks follows. Banks monitor their borrowers. By contrast, bondholders and stockholders are too dispersed to play such a role. Banks produce costly information in efficient markets, implying that banks profitability should at least cover the costs of information gathering (Grossman and Stiglitz, 1980). Banks smooth private consumption and agents are assumed to value such smoothness. Banks provide liquidity by converting short term deposit claims, which can be withdrawn without delay, to long term loans. This paper favors this last position. For a comprehensive survey of the literature see Gorton and Winton (2003).

The second question about the viability of banks opens a debate on the issue of bank panics and other banking crises. Why do these occur? Some authors believe that panics are unexpected events that arise from a sudden and irrational loss of depositor confidence, which is triggered randomly, and is referred to by mob psychology. This has been called the 'sunspot approach' to financial crises (Diamond and Dybvig, 1983; Diamond and Dybvig, 2000; and Diamond, 2007). Consequently financial crises cannot be and should not be theoretically modeled. On the other hand, other authors consider that bank crises emanate naturally over the business cycle (Allen and Gale, 1998). In recessions income of economic agents becomes lower, and hence consumption will fall if adjustment is not undertaken. And since agents try to smooth consumption they will withdraw from their deposits in times of recession in order to increase consumption, thereby putting stress on banks. It must be mentioned that Diamond and Dybvig (1983) make a connection between the liquidity function of banks and the ensuing bank panics. They state that providing more liquidity comes at the expense of eventual bank runs. The two are intimately related together. This paper takes the position of Diamond and Dybvig. A historical account of financial crises is provided in Kindleberger (1996).

The purpose of this paper is to estimate the probability of a bank run using the methodology of Diamond and Dybvig (1983) as modified by Allen and Gale (2009). The procedure is through Monte Carlo simulation by introducing uncertainty in the parameters of the theoretical model. This will be explained in more details in the third section, after the theory is presented.

Bordo et al. (2001) present a descriptive and thorough analysis of the frequency and duration of bank crises and other crises, like currency crises. They conclude that there is an annual frequency of 12.2%, or a one in eight chance, of observing a currency crisis, or a bank crisis, or a twin crisis, for the 56-country sample that they study for the post-1972 period. Dividing the period into two, they determine the annual probability to be respectively 8.8% and 5.6% for each period. Barro (2006) finds disaster probabilities of 2.18% for consumption and 1.92% for GDP. However Barro and Ursúa (2008), in a subsequent inquiry of macroeconomic crises since 1870, find higher disaster probabilities of 3.63% a year for consumption and 3.69% a year for GDP. Angkinand et al. (2010) estimate an average probability of a bank run of 5.1%. In addition these authors predict that this probability is between 0% and 5% for advanced nations. Since a prediction is not without error, the range, or confidence interval, for the probability of a bank run is definitely wider. All these estimates put bounds on a reasonable probability rate. The results in this paper show that the probabilities obtained by Monte Carlo simulation fall within the above ranges, and are closer to the lower limits than to the upper limits.

The second section reviews the theory behind this paper. The third section describes the simulation procedure. The fourth section presents and interprets the results. The fifth section undertakes sensitivity analysis and the last section concludes.

THE THEORY

As already mentioned the theory, on the basis of which this paper builds, is the one in Diamond and Dybvig (1983, 2000) as modified by Allen and Gale (2009). There are three periods, T=0, T=1, and T=2, and two productive or investment technologies. The first technology converts a dollar in T=0 to a dollar in period T=1. The second one converts a dollar in T=0 to $R > 1$ dollars in period T=2. Consumers are either early consumers, i.e. they consume in period T=1 with probability λ, or late consumers, i.e. they consume in period T=2, with probability $(1-\lambda)$. At time T=0 the consumer does not know which type he is, early or late consumer. This is revealed in period T=1. Without loss of generality the investment shares are y in the short term technology and $(1-y)$ in the long run technology. The long run asset can be liquidated for a price of 1 at T=1. Since $R > 1$ the long asset dominates the short asset and the bank will hold only the long asset. A time T=1 the bank liquidates $y = \lambda C_1$ to pay to early consumers where C_1 is consumption at time T=1. The bank maximizes the expected utility of the consumer, which takes the following form:

$$\lambda U\left(\frac{y}{\lambda}\right) + (1-\lambda)U\left(\frac{(1-y)R}{1-\lambda}\right) \tag{1}$$

The utility function $U(.)$ is isoelastic, with γ being the coefficient of relative risk aversion and C being consumption:

$$U(C) = \frac{C^{1-\gamma} - 1}{1-\gamma} \tag{2}$$

If $\gamma = 1$ in equation 2 the utility collapses to log utility. Some authors use the following utility function instead of equation 2:

$$U(C) = \frac{C^{1-\gamma}}{1-\gamma} \tag{3}$$

Equation 3 does not collapse to log utility when $\gamma = 1$. In this paper the correct utility function is used, i.e. equation 2.

The expected utility in equation 1, when a bank run is avoided, has the following solution (Allen and Gale, 2009: 80-81):

$$\lambda U(1) + (1-\lambda)U(R) \tag{4}$$

If there is a probability θ of a bank run in period T=1, and noting that in case of a bank run all consumers get a maximum of one dollar in period T=1 by sequential service, or by first-come first-served basis, then the expected utility is:

$$\theta U(1)+(1-\theta)\left\{\lambda U\left(\frac{y}{\lambda}\right)+(1-\lambda)U\left(\frac{(1-y)R}{1-\lambda}\right)\right\} \tag{5}$$

When there is a run expected utility is as in equation 5. When there is no run, expected utility is as in equation 4. When equation 5 is larger than equation 4 welfare enhancement imposes that the bank allows for a bank run. When equation 5 is smaller than equation 4 the bank will avoid a bank run. This paper estimates the expected utilities in equations 4 and 5 by Monte Carlo simulation, whereby all parameters are random or stochastic, i.e. all of $\lambda,\ \theta,\ y,\ and\ R$.

THE SIMULATION PROCEDURE

In equations 4 and 5 there are five unknowns. These are $\lambda,\ \theta,\ y,\ R$, and the utility function. In turn the utility function depends only on the value of γ. At first the value of γ is specified. It is modeled to take the following five different values: 1, 2, 3, 4, and 5, which represent the range of γ in the relevant literature. See, for example, the discussion in Azar (2011). Of course when γ is equal to 1 this leads to log utility. Once γ is specified the three parameters $\lambda,\ \theta,\ y$ are all simulated from uniform distributions that take a minimum of zero and a maximum of 1. Care is taken that these parameters are not simulated to be exactly equal to 1 or exactly equal to zero. The variable R is simulated from a uniform distribution that takes a minimum of 1.002 and a maximum of 1.083. The minimum of $(R-1)$ is 0.2% as determined in Azar (2008), while its maximum is 8.3% which is equal to the real rate of return on the portfolio of large stocks (Ross et al., 2010). I choose not to simulate R from a normal distribution in order to ensure a value always higher than 1 for R. The simulations are run 10,000 times, at the end of which the simulated probability of a run π is determined by taking the frequency with which equation 5 exceeds equation 4. Then the simulation is repeated 100 times, providing a sample of 100 for the simulated probability of a bank run π. The procedure is also repeated with a different value of γ. All in all there are five samples for π of 100 each, depending on the five assumed levels of γ. This simulation procedure allows for maximum uncertainty in the parameters.

THE RESULTS

Table I presents descriptive statistics and normality tests for the five samples. The point estimates of the mean probability of a bank run range between 3.54% and 5.36%. These are reasonable values. The upper value is for a γ of 2, and the lower value is for a γ of 5. Disregarding the case of log utility, the mean probabilities decrease with an increase in risk aversion γ. When log utility is assumed its mean probability lies in between.

The maximum probability of all maxima is 5.88%, and the minimum probability of all minima is 3.01%. The medians are very close to the means supporting symmetry of the distributions. Normality tests are undertaken in order to be able to measure confidence intervals. Five different normality tests are conducted. The Jarque-Bera normality test is well known and takes into consideration the skewness and the kurtosis of the distribution. The minimum p-value is 0.2358. This supports strongly normality. The other four tests are routinely calculated by the statistical package utilized, EViews 7.1. The null hypothesis for these four tests is normality. All these tests fail to reject normality, even at a marginal confidence level of 10%. Hence confidence intervals for the probability of a bank run π can be computed. The overall range of all confidence intervals lies between 3.18% and 5.80%. The overall range of all confidence intervals for the mean probability of a bank run $\bar{\pi}$ lies between 3.50% and 5.41%. See Table I for more details. Despite the simplicity of the model, the estimates of the probability of a bank run are all quite reasonable and the ranges are rather tight. This is testimony to the underlying theoretical model.

Table I. Descriptive statistics and normality tests of the probability of a bank run π across 5 coefficients of relative risk aversion (γ).

	$\gamma=1$	$\gamma=2$	$\gamma=3$	$\gamma=4$	$\gamma=5$
Number of simulation runs	100	100	100	100	100
Number of simulations per run	10,000	10,000	10,000	10,000	10,000
Mean (%) $\bar{\pi}$	4.1888	5.3639	4.4243	3.8919	3.5383
Median (%)	4.1850	5.3700	4.3950	3.8900	3.5350
Maximum (%)	4.7800	5.8800	5.0800	4.3300	4.0200
Minimum (%)	3.7200	4.9300	3.9000	3.5200	3.0100
Standard deviation (%)	0.1961	0.2198	0.2185	0.1741	0.1809
P-value of the Jarque-Bera normality test	0.4936	0.4766	0.2358	0.8315	0.9122
P-values of the following normality tests, with unknown parameters:					
Lilliefors (D)	> 0.1	> 0.1	> 0.1	> 0.1	> 0.1
Cramer-von Mises (W2)	0.7660	0.5718	0.2225	0.4841	0.5721
Watson (U2)	0.7802	0.5297	0.2905	0.4486	0.5267
Anderson-Darling (A2)	0.7790	0.5996	0.2542	0.3676	0.4022
95% confidence interval for π	3.804-4.573	4.933-5.795	3.996-4.853	3.551-4.233	3.184-3.893
95% confidence interval for $\bar{\pi}$	4.150-4.227	5.321-5.407	4.381-4.467	3.858-3.926	3.503-3.574

Note: the 95% confidence interval is ± 1.96 standard deviations, or ± 1.96 standard errors.

Table II presents two kinds of hypothesis tests on the mean probability of a bank run $\bar{\pi}$ across γ: a parametric t-test (panel A), and a non-parametric z-test (Wilcoxon-Mann/Whitney test, panel B).

For the two tests, and for all pair-wise comparisons, the test results are highly significant statistically. For the t-test the minimum t-value in absolute terms is 8.02. For the Wilcoxon-Mann/Whitney test the minimum z-value in absolute terms is 7.17. Since all these minimum values are much larger than the usual critical values, the conclusion is that the mean probabilities of a bank run differ significantly across γ. This means that it is important to specify a priori the parameter γ before adopting a probability of a bank run. However, and although the pair-wise comparisons support significant differences between $\bar{\pi}$, the estimates are all economically very close to each other. The reason for that is because the probability of a bank run π is estimated with very high precision.

On Table II, Pair-wise tests on the means of the simulation runs, or the means of the probabilities of a bank run ($\bar{\pi}$), across bilateral coefficients of relative risk aversion (γ). The results show that the following holds statistically significantly:

$$\bar{\pi}(\gamma = 2) > \bar{\pi}(\gamma = 3) > \bar{\pi}(\gamma = 1) > \bar{\pi}(\gamma = 4) > \bar{\pi}(\gamma = 5)$$

PANEL A:consists of T-tests on pair-wise independent samples. The test is a t-test. Tests on the variances reveal that all variances are equal except the variances of the probability of a bank run for $\gamma = 3$ with $\gamma = 4$, for $\gamma = 2$ with $\gamma = 4$, and for $\gamma = 2$ with $\gamma = 5$. When variances are equal pooled variances are computed. The degrees of freedom for the pooled variances are 198. The degrees of freedom for the unequal variances are 188.

THE EFFECTS OF CHANGES IN PRODUCTIVITY AND IN UNCERTAINTY.

This section undertakes sensitivity analysis to changes in average productivity and uncertainty. The three parameters λ, θ and y are restricted between 0 and 1. Hence, it is reasonable to simulate them with uniform distributions that have 0 as a minimum and 1 as a maximum. The coefficient of relative risk aversion (γ) is also an unknown. In this section log utility is assumed which implies a $\gamma = 1$. It is recalled that log utility simulations in Table I produced results that were in between the others. That is why log utility is assumed here.

Table II. Pair-wise tests on the means of the simulation runs					
PANEL A: T-tests on pair-wise independent samples.					
	$\gamma = 1$	$\gamma = 2$	$\gamma = 3$	$\gamma = 4$	$\gamma = 5$
$\gamma = 1$					
$\gamma = 2$	39.89				
$\gamma = 3$	8.02	-30.32			
$\gamma = 4$	-11.32	-52.50	-19.06		
$\gamma = 5$	-24.38	-64.13	-31.23	-14.08	
PANEL B: Wilcoxon-Mann/Whitney test. The test is a z-test					
	$\gamma = 1$	$\gamma = 2$	$\gamma = 3$	$\gamma = 4$	$\gamma = 5$
$\gamma = 1$					
$\gamma = 2$	12.22				
$\gamma = 3$	7.17	-12.19			
$\gamma = 4$	-9.16	-12.22	-11.67		
$\gamma = 5$	-12.07	-12.22	-12.20	-10.23	

The last parameter is R, the gross return on the long asset. Assuming a uniform distribution for R is not totally satisfactory. Hence changes in R need to be allowed. Assume that the uniform distribution is identified by its maximum b, and by its minimum a. The first moment of such a distribution, which is its mean μ, is equal to:

$$\mu = \frac{(b+a)}{2} \tag{6}$$

The second moment of this same distribution, which is its variance, is equal to:

$$\sigma^2 = \frac{(b-a)^2}{12} \tag{7}$$

Looking at equations 6 and 7 it is clear that, if b and a are both increased by the same amount, the variance does not change, while the average becomes higher. The average in this case is $\bar{R}$, the average productivity, and the variance is an estimate of the uncertainty in productivity or in R. It is worthwhile to consider two cases. The first case is when the average productivity increases, keeping the variance or uncertainty constant. The second case is when both the average productivity and the uncertainty are changed together. For the first case both a and b are increased either by 2% or by 4%. This will leave the uncertainty to be the same. For the second case a alone is increased either by 2% or by 4%.

Given these changes in average productivity and in uncertainty the simulations are rerun as carried out previously. In other terms 100 runs of 10,000 simulations each are generated for the four cases at hand. In these simulations λ, θ and y are still generated from uniform distributions between 0 and 1, and R takes the 4 new uniform distributions identified above. The base case is log utility as simulated in Table I (2nd column).The results are summarized in Table III.

Before looking at the empirical results a mention should be made about the expected effects of these changes in b and a on the average probability of a bank run. Higher uncertainty is expected to lead to a higher average probability of a bank run. However the effect of higher productivity on this average probability is less intuitive. One might expect a negative relation. As a matter of fact the relation should be positive because of the following reason. As average productivity increases banks have the incentive to liquidate more of the long asset if they want to keep consumption at the same level at time T=2. This implies that $(1-y)$ is smaller, and that y is higher. A higher y makes $\lambda C_1 = y$ closer to 1, where C_1 is consumption as T=1. As $\lambda C_1 = y$ reaches the 1evel of 1 nothing is left to late consumers, and hence there is obviously a bank run. This explains why higher average productivity increases the average probability of a bank run.

Table III consists of descriptive statistics and normality tests of the probability of a bank run π when productivity and uncertainty are modified. The coefficient of relative risk aversion (γ) is assumed to be equal to 1, which implies log utility.

The empirical results that are summarized in Table III corroborate the expected outcomes. When average productivity is higher, and uncertainty is left constant, the probability of a bank run is higher on average (columns 3 and 4 in Table III). Moreover a higher change in productivity leads to a higher probability of a bank run as the t-test and Wilcoxon-Mann/Whitney test show. The test statistics for the hypothesis that the average probability of a bank run is higher the higher is the increase in average productivity are respectively 9.79 and 8.29 for the two tests.

When average productivity is increased and uncertainty is decreased at the same time the effect of uncertainty dominates and the average probability of a bank run is lower. See columns 4 and 5 in Table III. Nonetheless when the result of an increase in a by 2% is compared to the result from an increase by 4%, the probability of a bank run is on average the same statistically. The test statistics for the hypothesis that the mean difference is zero are -1.28 and -1.30 for the t-test and Wilcoxon-Mann/Whirney test respectively. Hence the hypothesis that the effect of an increase in a is the same for an increase of 2% and for an increase of 4% fails to be rejected. It seems that with a 4% increase in a the effect of a higher productivity, from 2% to 4%, offsets partially the effect of a lower uncertainty, from 2.338% to 1.184%. In this latter case, the average probability of a bank run is still higher than for the base line: compare columns 2 and 6 in Table III.

Table III. Descriptive Statistics and Normality Tests					
	R : 1.002 to 1.083	R : 1.022 to 1.103	R : 1.042 to 1.123	R : 1.022 to 1.083	R : 1.042 to 1.083
Average productivity rate $(\overline{R}-1)$	4.25%	6.25%	8.25%	5.25%	6.25%
Uncertainty (std. dev.)	2.338%	2.338%	2.338%	1.761%	1.184%
Number of simulation runs	100	100	100	100	100
Number of simulations per run	10,000	10,000	10,000	10,000	10,000
Mean (%) $\overline{\pi}$	4.1888	4.1610	4.4341	3.7102	3.6766
Median (%)	4.1850	4.1500	4.4500	3.7250	3.6600
Maximum (%)	4.7800	4.6900	4.9300	4.1500	4.1500
Minimum (%)	3.7200	3.6700	3.9100	3.3400	3.2600
Standard deviation (%)	0.1961	0.1955	0.1943	0.1819	0.1879
P-value of the Jarque-Bera normality test	.4936	.7608	.7899	.4427	.6625
P-values of the following normality tests, with unknown parameters:					
Lilliefors (D)	> 0.1	> 0.1	> 0.1	> 0.1	> 0.1
Cramer-von Mises (W2)	0.7660	0.1756	0.2437	0.5072	0.6916
Watson (U2)	0.7802	0.1557	0.2112	0.4655	0.6802
Anderson-Darling (A2)	0.7790	0.2868	0.2142	0.5126	0.7697
95% confidence interval for π	3.804-4.573	3.778-4.544	4.053-4.815	3.354-4.067	3.308-4.045
95% confidence interval for $\overline{\pi}$	4.150-4.227	4.123-4.199	4.396-4.472	3.675-3.746	3.640-3.713
t-test		0.89	8.88	-17.89	-18.86
Wilcoxon-Mann/Whitney test		0.82	7.71	-11.40	-11.50
Note: the 95% confidence interval is ± 1.96 standard deviations, or ± 1.96 standard errors. The test statistics are reported for the two tests, i.e. the t-test and the Wilcoxon-Mann/Whitney test. All tests are relative to the data in column 2.					

CONCLUSION

This paper started with a theoretical model for a bank that is assumed to be a liquidity provider (Diamond and Dybvig, 1983; Diamond and Dybvig, 2000; and Diamond, 2007). The model is modified and simplified by Allen and Gale (2009). Building on these references, the expected utility when a bank avoids a run is derived theoretically. Also is derived theoretically the expected utility when a bank run is allowed with a finite probability. Because of welfare considerations, when the latter utility turns out to be higher than the first, then a bank run is a possibility. There are five unknowns in the model. Besides the form of the utility function, all the other four unknowns are simulated from appropriate uniform distributions. For each utility function 10,000 simulations are replicated 100 times. Five utility functions are assumed. The results show that the mean probability of a bank run depends statistically on the coefficient of relative risk aversion, and is estimated very precisely. However, all mean probabilities are economically very close to each other. The widest range for the probabilities lies between 3.18% and 5.80%. The widest range for the means of the probabilities lies between 3.50% and 5.41%. These ranges are reasonable by all standards, and are comparable to the estimates in the literature. This is testimony to the fact that the model used, while quite basic and simple, can produce nevertheless sensible and realistic estimates.

At the end a sensitivity analysis to changes in average productivity and in uncertainty is undertaken. The results are as expected. A higher average productivity leads to a higher probability of a bank run. A lower uncertainty leads to a lower probability of a bank run. The intuition for these effects is explained in the text. When both average productivity and uncertainty are changed in opposite direction there is a partial offset in the net effect.

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TOO BIG TO FAIL?
SIZE AND RISK IN BANKING

Mitchell Stan, The Open University
Michael L. McIntyre, Carleton University

ABSTRACT

The recent global financial crisis has raised important questions about governments' "too big to fail" policies and their potential impact on bank risk-taking. It is now clear that certain banks in almost all countries are considered to be too big to fail and will receive taxpayer-funded bailouts if failure appears imminent. An important question that arises is whether larger banks, that enjoy this status, have in fact taken on more risk than their smaller counterparts who face much more credible threats of wind-up or bankruptcy should they get into financial difficulty.

This study confirms that larger banks take on higher levels of risk than smaller ones and this finding persists when returns are measured before interest and taxes. The higher risk levels are driven by the lower capital to assets ratios and higher variances in return on assets of the larger banks. There is some evidence that large banks also generate higher returns on assets. The findings will be of interest to regulators and central banks since they can potentially contribute to better allocation of supervisory resources and more appropriate intervention strategies, such as requiring these riskier large banks to hold higher levels of capital or to pay additional taxes as has been proposed by the International Monetary Fund. This study appears to be the first using this methodology on a sample of banks that ranges from the very smallest to the very largest and includes both publicly-traded and privately-owned institutions.

INTRODUCTION

The recent global financial crisis has raised questions about governments' "too big to fail" policies and their impact on bank risk-taking. It is now clear that certain banks in almost all countries are considered to be too big to fail and will receive taxpayer-funded bailouts if failure appears imminent. An important question therefore is whether larger banks, that enjoy this status, do in fact take on more risk than their smaller counterparts. If so, as Ennis & Malek (2005 p.21) point out, the "expectation of contingent bailouts tends to create efficiency costs in the economy." Further, measures such as those proposed by the International Monetary Fund to place a levy on large banks to cover the costs of their failures to taxpayers could be more strongly justified (Braithwaite, 2010). There is an opposing theory, though, that suggests the economies of scale and scope larger banks enjoy enable them to achieve greater levels of diversification and lower marginal costs for risk reducing investments such as in information technology, collection and internal audit departments with the overall result that they take on less risk than their smaller counterparts. Research on the question of whether there is a positive or negative relationship between bank size and risk is, as described below, not clear-cut and most of it to date focuses on larger, publicly-traded banks.

This paper, therefore, takes another look at whether large banks are in fact riskier using a methodology that has not yet been applied to this question using a ratio, which we call the risk index, that incorporates capital levels, returns on assets and the variability of those returns into one measure. The data set includes a wide variety of banks from the smallest to the largest, both publicly-traded and privately-owned. The findings will be of interest to regulators and central banks since they can potentially contribute to better allocation of supervisory resources and more appropriate intervention strategies, such as requiring these riskier banks to hold higher levels of capital. A better understanding of the risk and return characteristics of banks would be beneficial for regulators and central banks interested in the stability of the banking system due to costs involved with bank failures, the possibility of systemic risk and potential disruptions in the availability of credit. Deposit insurers concerned with minimizing their losses and assessing premiums according to risk could also benefit.

The results of this study provide evidence in support of larger banks being more risky. The larger categories of banks have higher variances in returns on assets and lower capital to assets ratios than the smaller ones. Their somewhat higher levels of returns on assets are not sufficient to counterbalance these two factors in the risk index, which is a compound measure including measures of profitability, capitalization, and risk taking. In fact, this higher level of returns may be another result of more aggressive risk-taking on the part of these larger banks.

LITERATURE REVIEW

There are theoretical reasons and empirical support for both positive and negative relationships between size and bank risk. On one hand, larger banks may perceive themselves, and be perceived by others, to be "too big to fail" because of their systemic importance and therefore expect to be bailed out by governments if they run into trouble; consequently they may take on excessive levels of risk. The effect is amplified by the existence of deposit insurance if premium payments do not accurately reflect the underlying risk, which is the case in the US and in most other countries due to the difficulties involved in pricing deposit insurance. This means that while gains from growth or pursuing risky strategies go to bank shareholders, losses are borne by the government through the deposit insurer. Boyd & Graham (1986 p.4) described the payoff facing shareholders of banks with deposit insurance as "Heads we win, tails, the FDIC loses". Bank size may also be linked to higher risk because of agency problems associated with managing a larger and more complex organization (Elyasiani et al, 2007).

While the direction of the relationship between size and risk of banks has been extensively researched most studies focus on larger, publicly-traded banks or bank holding companies. Demsetz & Strahan (1995) and Chen et al (2011), for example, reported inconclusive results about the relationship between size and risk with large bank holding companies taking on higher levels of systemic risk but offsetting this with lower levels of firm-specific risk meaning that total risk was not related to asset size. In the 1995 study there were some indications that this might be changing after 1991 as the larger firms started to take on lower levels of systemic risk and thus lower levels of overall risk. Demsetz & Strahan (1997) found similar results to their earlier 1995 study with the risk-reducing benefits of diversification available to the larger banks being offset by lower capital levels and the tendency to pursue riskier activities such as commercial and industrial lending. All three of these studies looked only at publicly-traded companies.

An international study, also on publicly-traded banks, in 21 industrialized countries for the period 1988-1998 found that small banks are riskier than large ones (De Nicolo, 2000). The only sub-sector where this finding did not apply was to the smallest category of US banks. In contrast De Nicolo et al, (2004), found that large financial conglomerates exhibited a higher level of risk in 2000 than their smaller counterparts, although this trend was not apparent in 1995. They attributed the 2000 result to moral-hazard incentives outweighing the potential risk-reducing effects of geographic and product diversification, and economies of scale and scope. In 2000, the larger financial firms had both lower levels of capital relative to assets and larger standard deviations of returns on assets. Results were the same for sub-samples of banks from the US, Japan and Western Europe.

Some previous studies did include both private and publicly-traded banks but did not look directly at risk in the manner of this study. Instead they used accounting or other measures in isolation as their risk metric. McAllister & McManus (1993) found that larger banks tend to operate with lower capital ratios and found a negative correlation between loan portfolio size and variance of returns. Boyd & Graham (1996) report that larger banks were more prone to failure than smaller ones. When failure was broadly defined as including those banks that are in receipt of government funds in any form of bailout, the large American bank failure rate was much higher in both the periods 1971 to 1978 and 1979 to 1986, while small banks failed more commonly in the period 1987 to 1994. In the overall period of 1971 to 1994, though, the large bank cumulative failure rate was higher at 17% compared to 12% for the smaller banks. The authors theorized that the too big to fail doctrine may play a role in explaining these findings. Stiroh (2004) reported that for small community banks with less than $300 million in assets, increased size was positively associated with higher returns and lower standard deviation of those returns, which he attributed to benefits from economies of scale or geographic diversification. His findings may not be generalizable to the entire universe of banks however, as he looked at only a subset of very small banks.

Boyd and Gertler (1994), using data from 1983 to 1991, reported that large banks, especially those with over $10 billion in assets were riskier as they had lower returns on assets but also held substantially lower levels of capital than their smaller counterparts. They also found a u-shaped pattern in the loan loss provision ratio, with the largest banks performing worst on this measure. Large banks were also riskier on the liability side of the balance sheet depending more heavily on volatile money market instruments rather than the more stable core deposits that smaller banks relied on. They concluded that the robust negative correlation between size and performance may be indicative of an increased perception of a too big to fail subsidy.

Ennis and Malek (2005) developed a simple model of the too big to fail effect and examined whether its implications were supported by empirical evidence. They hypothesized that large banks that are riskier ex ante, are also more likely to perform poorly ex post as these banks, encouraged to take risks, would have a larger variance of returns and thus be more likely to fail. Overall, their findings were inconclusive with the data from certain time periods supporting their hypothesis and data from other periods contradicting it. Return on assets was related positively to size, increasing reliably between each of their six size categories ranging from under \$50 million in assets to over \$10 billion. While Boyd & Gertler (1994) and Ennis & Malek (2005) reported results for returns on assets and capital to asset ratios, they did not report risk index scores as this study does.

Overall, therefore, the literature is not unanimous but does lean towards the view that larger banks are riskier because of lower capital levels combined with higher variances of returns on assets which are not totally offset by their higher returns on assets.

The primary risk measure in this study is the risk index. This is a measure that has been commonly used in the literature (e.g. Hannan & Hanweck, 1988; Sinkey & Nash, 1993; Boyd et al, 1993; Kwan & Laderman, 1999; and Beck & Laeven, 2006). It is calculated as:

$$Risk\ Index = \frac{\left(\left(\frac{\Pi}{A}\right)+\left(\frac{K}{A}\right)\right)}{\sigma\Pi/_A}$$

In this equation Π is net income, *A* is total assets and *K* is total regulatory capital held by the bank. The risk index has been widely and regularly used as a proxy for risk in the financial and non-financial literature since Roy (1952). It has commonly been referred to as the distance-to-default and the z-score but differs from Altman's (1968) z-score which is a predictor of corporate financial distress based on accounting ratios. The risk index incorporates profitability, return volatility and leverage into one measure.

Studies utilizing the risk index include: Boyd & Graham (1996) who looked at the relationship between risk and the degree of involvement in non-bank activities; Hannan & Hanweck (1988) who investigated whether there was, as they expected, a positive relationship between bank risk-taking and the spreads over the default free rate and Kimball (1997) who compared banks specializing in small business micro-loans with a mixed peer group matched by size and location and found that the focused group was riskier than the diversified group. Eisenbeis & Kwast (1991) used the risk index to compare banks specializing in real estate lending with their more broadly diversified counterparts and found little difference between the two. In contrast to that study, Liang & Savage (1990) found that focused companies had higher risk levels than their diversified control group. Sinkey & Nash (1993) used the risk index to compare banks focusing on credit cards with those pursuing a diversified strategy. They found that the credit card banks were riskier despite generating higher returns than their more diversified counterparts.

DATA AND METHODOLOGY

We have chosen an accounting measure of risk in the form of the risk index rather than a market-based measure because only a very small minority of banks in the United States are publicly-traded. In order to better understand the underlying drivers of the level of risk we also examine the subcomponents of the risk index: returns on assets, variances of those returns and capital levels for various sizes of banks. Capital levels in particular are also of interest since the FDIC charges banks for deposit insurance in large part based on the levels of capital they hold and, under the FDIC Improvement Act (FDICIA) of 1991, banks whose capital ratio falls below 2 percent face closure if the shortfall is not corrected within 90 days (Ennis & Malek, 2005).

While accounting data is, at best, a proxy that emulates some underlying economic reality, research has shown that accounting earnings and stock market data are statistically positively related (Rivard & Thomas, 1997). Accounting data for banks also have the advantage of being more uniform than that of other industries due to the presence of regulator-mandated reporting requirements.

Returns in this study are measured relative to total assets rather than relative to equity to minimize the impact of leverage which for banks can be very substantial, and can vary considerably between banks. Further, they are a direct measure of management's ability to generate returns on a portfolio of assets (Rivard & Thomas, 1997). In an additional effort to isolate the leverage impact, returns are also calculated on a before interest and taxes basis.

While the risk index has its advantages, shortcomings must also be noted. First, it measures risk in a single period of time and therefore does not take into account the potential for higher levels of risk resulting from a sequence of losses over more than one period. It also relies on the accuracy of accounting data, which may not be a well-founded assumption since the literature indicates that banks tend to smooth earnings (Beck & Laeven, 2006). Notwithstanding these concerns, the risk index still can be a useful measure of relative risk between groups of banks at a point in time.

Hannan and Hanweck (1988) explained their derivation of the risk index by pointing out that insolvency for banks occurs when current losses exhaust capital or, equivalently, when the return on assets is less than the negative capital-asset ratio. They go on to show that the probability of insolvency is:

$$p \leq (1/2)\frac{\sigma^2}{\left(E\left[\frac{\Pi}{A}\right]+\frac{K}{A}\right)^2}$$

The ½ in this inequality accounts for the fact that failure occurs only in one tail of the distribution. If profits follow a normal distribution then the risk index is the inverse of the probability of insolvency. It measures the number of standard deviations that a bank's return on assets has to drop before equity is wiped out (Beck & Laeven, 2006). Because of this relationship, the risk index has sometimes been referred to as the probability of failure (see, for example, Kwan & Laderman, 1999).

Even if returns on assets are not normally distributed, the risk index is still useful for relative comparisons (Boyd et al, 1993). It likely underestimates the true probability of bankruptcy since, by definition, it assumes failure only if one-period losses exceed a bank's total capital. Realistically though, banks experiencing losses of a much smaller scale could experience liquidity problems, creditor runs and regulatory interventions (Boyd & Graham, 1986).

This study appears to be the first examining the relationship between size and risk for a sample of banks that ranges from the very smallest to the very largest and includes both publicly-traded and privately-owned institutions. We examine this important issue, using the risk index, through the following four hypotheses:

H_1 *Total risk, measured by the risk index, is higher for the larger banks than for the smaller ones.*

H_2 *Returns measured relative to total assets are higher for the larger banks than for the smaller ones.*

H_3 *Volatility risk, measured by the standard deviation of return on assets, is higher for the larger banks than for the smaller ones.*

H_4 *The capital-asset ratio is lower for the larger banks than for the smaller ones.*

For each quarter-end for the period from December 31, 2001 to December 31, 2008 three different data values were obtained for each bank: return on assets, average assets and the capital to assets ratio. Return on assets is defined both as net income after taxes and extraordinary items (annualized) as a percent of average total assets and before taxes and interest as a percent of average total assets. Assets are the sum of all assets owned by the institution including cash, loans, securities, bank premises and other assets but do not include off-balance-sheet accounts. The capital to assets ratio is calculated as Tier 1 or core capital as a percent of average total assets minus ineligible intangibles. Tier 1 capital includes: common equity plus noncumulative perpetual preferred stock plus minority interests in consolidated subsidiaries less goodwill and other ineligible intangible assets. The amount of eligible intangibles (including mortgage servicing rights) included in core capital is limited in accordance with supervisory capital regulations. Average total assets used in this computation are an average of daily or weekly figures for the quarter.

Mean returns on assets and the mean capital to assets ratios were calculated as the mean of the quarterly observations during the twenty-eight quarter study period for each bank. Similarly the standard deviation of return on assets was based on the quarterly observations of returns during the twenty-eight quarter study period for each bank and the mean of the observation as discussed above.

Data for the study were obtained from the Statistics on Depository Institutions website of the Federal Deposit Insurance Corporation at www2.fdic.gov/sdi/index.asp. This database includes balance sheet, income statement, condition and performance ratios, and demographic information for all federally regulated American banks, trust companies and savings and loan institutions. To avoid the impact of failures and new bank start-ups on data consistency, only banks that had the same FDIC number and had information available for all quarters in the observation period were included in this study.

EMPIRICAL FINDINGS

There were 7,369 banks in existence for the full period in the FDIC database. The largest was JPMorgan Chase Bank with $962 billion in average assets, and the smallest was The Oakwood State Bank with under $3 million in average assets during the study period. We use the same size categories as in Boyd & Gertler (1994) and Ennis & Malek (2005). Hypothesis one is that risk, as measured by the risk index, is higher for the larger banks than for the smaller ones. Before discussing Table 1 it is important to note that the higher the risk index score, the lower the risk. The results show, as hypothesized, a generally increasing trend in risk as bank size increases above $250 million in assets. A Mann-Whitney test on the log of the risk index scores confirms that the difference is statistically significant at the 1% level for all comparisons between the largest and second largest size categories and all of the smaller categories. A log transformation was used for this test because the raw risk index score did not meet the equal variance distributional requirement. The right hand column of Table 1, entitled EBIT Risk Index, shows the risk index calculated with return on assets on a before interest and taxes basis. The same trend is apparent and the Mann-Whitney test on the log of the risk index scores again confirms that the difference is statistically significant at the 5% level for comparisons between the three largest size categories.

Table 1: Risk Index and EBIT Risk Index by Bank Asset Size Category			
Average Assets Size Category	Sample Size	Risk Index	EBIT Risk Index
Over $10 billion	83	27.0	22.1
Over $1 billion to $10 billion	388	37.0	25.0
Over $250 million to $1 billion	1,543	44.2	28.4
Over $100 million to $250 million	2,141	47.6	30.3
Over $50 million to $100 million	1,683	46.1	31.6
Under $50 million	1,531	46.1	34.0

Hypothesis two is that returns on assets are higher for the larger banks than for the smaller ones. There was some support for the second hypothesis as shown in Table 2 below. The two largest groups of banks, with more than $1 billion and more than $10 billion in average assets respectively had the highest and second highest returns on assets of the six groups. Although this is the case, only the differences between the two largest and the smallest size category of banks were statistically significant at the 5% level.

Hypothesis three is that the standard deviation of returns on assets is higher for the larger banks than for the smaller ones. The evidence, also shown in Table 2 below, generally supports this hypothesis. The group of largest banks, with more than $10 billion in average assets, had the highest standard deviation of returns with the second largest group ranked second. Overall, the relationship was U-shaped with larger and smaller groups having higher variances than mid-sized banks. All of the differences were statistically significant at 5% with the sole exception of that between the banks holding between $50 and $100 million in assets and those with between $1 billion and $10 billion.

Table 2: Return on Assets, Variance of Returns and Capital to Asset Ratios by Bank Asset Size Category			
Average Assets Size Category	Annualized Percentage Return on Assets	Standard Deviation of Returns on Assets	Percentage Capital to Assets Ratio
Over $10 billion	1.1483	1.3162	15.3
Over $1 billion to $10 billion	1.2731	1.1692	15.3
Over $250 million to $1 billion	1.0507	0.7853	15.4
Over $100 million to $250 million	1.0676	0.7433	16.7
Over $50 million to $100 million	0.9917	0.7603	18.7
Under $50 million	0.9943	1.1607	28.6

Hypothesis four is that the capital to assets ratio is lower for the larger banks than for the smaller ones. This hypothesis is strongly supported with the smaller banks holding significantly more capital relative to assets than the larger banks. Mann-Whitney tests on the differences between the largest group of banks with more than $10 billion dollars in average assets during the study period and each of the other size categories was statistically significant at the 1% level in each case except for the comparison to the second largest group.

CONCLUDING COMMENTS

The data provide strong support for the hypothesis that larger banks are riskier than smaller ones during the period 2001 to 2008 with one of the major contributing factors being their lower levels of capital relative to assets. The larger banks generally also have higher returns on assets than the smaller ones. This finding is in contrast to Boyd & Gertler (1994) who found that from 1984-1991 larger banks had lower returns on assets than the smaller ones but it concurs with Ennis & Malek (2005) who found that from 1992 to 2003 return on assets was positively related to size. While these higher returns would likely be viewed positively by management and shareholders, they also may be a sign of higher levels of risk-taking for example, by moving from prime to sub-prime mortgages.

In 2009, stress tests were conducted by regulators on nineteen large banks with more than $100 billion in assets, implicitly identifying them as qualifying under the doctrine of too big to fail. During the study period covered by this paper only eight banks had more than $100 billion in assets. These largest banks had a mean risk index score of 28.0, almost as low as the largest group discussed in the main section of this paper with over $10 billion in assets, which had a score of 27.0 indicating higher levels of risk. When the risk index was calculated using return on assets before taxes and interest these largest eight banks had a lower risk index score of 20.1 than the largest group discussed which had a score of 27.0. They also had similarly low levels of capital to assets at 11.5%, and high levels of returns on assets and standard deviation of returns at 1.15% and 0.4949, respectively. This supports the view that this sub-set of extremely large banks also tends to carry higher levels of risk than the smaller ones.

Given recent turbulence in financial and banking markets, regulators such as the Federal Reserve Board have been increasingly attracted to the idea of using regulation selectively and aggressively to target specific excesses (Guha, 2008). A better understanding of the relationship between bank size and risk and the relative risk of various sizes of banks would be beneficial as it could lead to better allocation of regulatory resources towards higher risk banks by regulators and deposit insurers. Banks in higher risk categories could be subject to more frequent and more intensive on-site and off-site monitoring. Larger banks posing higher levels of risk to the financial safety net could be required to hold higher levels of capital, pay higher deposit insurance premiums, or engage in other activities such as the purchase of credit default protection in order to mitigate that risk. Obviously, the benefits of these types of measures would have to be weighed against potential costs including direct expenditures and the hindrance of competition and innovation in the banking sector.

Research into the sub-component ratios of the risk index would also have value. For example, an examination of why the larger banks exhibit higher standard deviations of return on assets would be beneficial. Further, other capital ratios such as tangible capital, which is often utilized by credit rating agencies, may be more effective than the measure utilized here. The length of time over which the standard deviation of returns should be measured could also benefit from sensitivity analysis to evaluate overall effectiveness.

Investigation into how bank efficiency is related to risk also would be useful. The literature shows that efficiency, capital and risk are all interrelated. Altunbas et al (2007) for example, have shown that inefficient European banks hold more capital than more efficient ones. As they point out, though, different hypotheses about the link between capital, risk and efficiency exist. It is possible that regulators allow well-managed banks, as demonstrated by their efficiency, to operate with lower levels of capital. On the other hand, poorly managed, inefficient firms may take on riskier loans in an attempt to boost profitability. Also, a bank may choose to boost short-term profits through reducing budgets for loan underwriting and monitoring thus boosting short-term profits and creating a positive link between efficiency and risk at least in the short-term. A better understanding of these relationships would be beneficial.

Extensions of this type of study into other countries and time periods would be valuable. The period examined here was a relatively benign one for the banking industry and may not be representative of all eras. The American banking industry, with its large number of very small banks, is also unique in the world and for these two reasons the results described here may not generalize to other countries.

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MULTIVARIATE MARKOV MODELS FOR RETAIL MORTGAGES BASED ON CORRELATION ANALYSIS

Chang Liu, SouthernWest University of Finance and Economics, China
Morsheda Hassan, Wiley College
Raja Nassar, Louisiana Tech University
Min Guo, China Banking Regulatory Commission, Sichuan Branch, China

ABSTRACT

Regional banks usually issue financial credit products such as mortgages and credit cards to the same group of local residents. As a result, the health correlation analysis for those different credit products is necessary both for more accurate default prediction and credit policy establishment. The goal of this study is to present a high-order multivariate Markov chain model to analyze the relationship between the payment behaviors of retail mortgage loans and consumer credit cards (other than commercial cards) by analyzing the delayed (and therefore high-order) cross products and therefore multivariate transition processes between mortgages and credit cards. This model provides a theoretical basis for the empirical phenomenon concerning the historically high correlation between those two retail financial products. Also, it provides the bank management with a quantitative method to predict its loans' behaviors, which is important for making strategic financial decisions.

INTRODUCTION

The financial crisis in 2008 has witnessed the phenomenon of high default correlations among credit products issued by banks such as retail mortgages loans and credit cards. During the second half of 2008, the banks experienced the co-downward-shift of health distributions for the above two products. From an economic point of view, this phenomenon could be largely due to the fact that under macro-economic factor shocks, such as the decease in GDP growth rate and high unemployment, consumers with low income and unstable jobs might find themselves in a position where they are unable to make the scheduled monthly payments for their mortgages. Hence, under such a circumstance, they might use their credit cards to meet the mortgage contract requirement at a much higher cost. Mortgage rates are usually between 3%-5% depending on consumers' credit scores and other relevant background information, while the interest rate for a late payment amount seldom is lower than 7%. As a result, the consumers, resorting to a higher cost financing option with credit cards just to buy more time to pay back the lower cost mortgage payment, would have further difficulties in keeping their property,

especially if the macro-economy deteriorates further. Under a severe circumstance, such as the crisis in 2008, massive defaults and losses both for mortgages and credit cards could be expected. Thus, it would be reasonable and necessary to keep tracking the correlation between credit products payment in order to build an early warning system for bank credit portfolios.
The analysis of correlation between credit products, however, is one of the most difficult tasks confronting a credit risk professional. This may be due to the lack of sufficient observations and/or a good predictive model. A model enables one to analyze and predict the default and delinquency behavior in different but related credit products offered to the same group of customers. Therefore, a correlation analysis is of particular importance for small community lending institutes whose customers are composed of local relatively stable group of residents.

The purpose of this research is to use multivariate Markov chain models to analyze and predict the default and delinquency behavior for mortgage loans by taking the correlation between mortgage loans and credit cards into account. It is realized that although the prepayments among mortgage loans could be substantial, if there is no prepayment penalty term in the contract, the prepayment for credit card is practically non-existing. As a result, a transition between any state of a mortgage loan and a prepaid state in credit cards should be zero.

In this study, we develop a multivariate Markov chain model (first-order and higher-order) for mortgages and credit cards and a higher-order univariate Markov chain model for mortgage loans. Furthermore, we compare these three models with regard to prediction accuracy.

LITERATURE REVIEW

The basic property of a Markov chain has been extended to accommodate many new applications, among them are traffic analysis in the network, speech recognition, DNA sequences analysis, engineering designs, and inventory management. Also, new theories extending the basic Markov assumption have been developed in the past 50 years, such as High-order Markov chains and Multivariate Markov chains. These important developments are introduced in the following subsections.

Higher-order Markov chains

Higher-order Markov chains assume that not only the immediate past random variable but also the past k variables, or kth order, have significant effects on the current one. That is, $\Pr(X_{n+1} = x \mid X_n = x_n, ..., X_1 = x_1, X_0 = x_0) \neq \Pr(X_{n+1} = x \mid X_n = x_n)$. It is difficult to solve the problem directly because the number of parameters to estimate increases exponentially with the order of the model.

Wang (1992) showed that one needs 7 parameters to completely specify the transition intensitiesof a second-order two state Markov chain. This is shown as follows:

$$\begin{aligned}
&\Pr(X_{i+1} = 1 \mid X_{i-1} = 0, X_i = 0) = \alpha_1, \\
&\Pr(X_{i+1} = 1 \mid X_{i-1} = 1, X_i = 0) = \alpha_2, \\
&\Pr(X_{i+1} = 0 \mid X_{i-1} = 0, X_i = 1) = \beta_1, \\
&\Pr(X_{i+1} = 0 \mid X_{i-1} = 1, X_i = 1) = \beta_2, \\
&\Pr(X_2 = 0 \mid X_1 = 1) = z_1, \\
&\Pr(X_2 = 1 \mid X_1 = 0) = z_2, \\
&\Pr(X_1 = 1) = \tau
\end{aligned} \tag{1}$$

Generally, one can verify that a $k \cdot th$ order sequence with S states will have $(S-1) \cdot S^k$ parameters. Thus, industrial application of higher-order Markov chains has been hampered by this problem. Raftery (1985), however, proposed a higher-order Markov chain model with only one parameter for each extra lag. By assuming that $\sum_{i=1}^{k} \lambda_i = 1; \lambda_i \geq 1, i = 1, 2, ..., k$, his model is expressed as

$$\begin{aligned}
&P[X_t = j_0 \mid X_{t-1} = j_1, ..., X_{t-k} = j_k] = \sum_{i=1}^{k} \lambda_i q_{j_0 j_i} \\
&0 \leq \sum_{i=1}^{k} \lambda_i q_{j_0 j_i} \leq 1
\end{aligned} , \tag{2}$$

where $q_{j_0 j_i}$ is the transition intensitiy from state j_0 to state j_1.

In matrix form, the model is given as

$$\hat{X}_t = \sum_{i=1}^{k} \lambda_i Q X_{t-i} \tag{3}$$

where $X_t = (x_t(1), ... x_t(m))^t$, $x_t(j) = 1$, if $X_t = j$ and equal to 0 otherwise, and $\hat{X}_t = (\hat{x}_t(1), ... \hat{x}_t(m))^t$, where the random variable $\hat{x}_t(j)$ is a function of past values and could be represented as: $P[X_t = j_0 \mid X_{t-1} = j_1, ..., X_{t-k} = j_k]$.

To estimate the parameters, Raftery (1985) applied the maximum log-likelihood technique

$$L = \sum_{i_0, ... i_k = 1}^{m} n_{i_0, ..., i_k} \log(\sum_{j=1}^{k} \lambda_j q_{i_0, i_j}) \text{ ,where } n_{i_0, ..., i_k} = \sum_t x_t(i_0) x_{t-1}(i_1) ... x_{t-k}(i_k).$$

He applied this method to a 4th order model in analyzing the wind power in a wind turbine design problem. By comparing model results for different orders, he concluded that the 4th order was the best model as it gave the smallest Bayesian information criterion (BIC) value, where

$$BIC = -2L + k \log n .$$

Berchtold and Raftery (2002) extended a finite space mixture transition distribution (MTD) model (Raftery, 1985) to deal with an Infinite Denumerable State Space and demonstrated a variety of applications including DNA sequence and financial time series. Similar models have also been studied by Berchtold (2001).

Another Higher-order model was proposed by Ching and Ng (2006). Assuming $\lambda_i, i = 1, 2..., k$ are non-negative and $\sum_{i=1}^{k} \lambda_i = 1$, Ching and Ng generalized Raftery's model by allowing the transition intensitiy matrix Q to vary with different lags. Written in matrix form, Ching and Ng's model could be expressed as

$$X^{(n+k+1)} = \sum_{i=1}^{k} \lambda_i Q_i X^{(n+k+1-i)} \tag{4}$$

If we let $Q_1 = Q_2 = ... = Q_k$, Ching and Ng's model in Equation (5) reduces to Raftery's model in Equation (3). They used linear programming method to estimate the parameters which could be done in Microsoft Excel® with the built *Solver()* function:

$$\begin{cases} Min_\lambda \{ \left\| \sum_{i=1}^{k} \lambda_i V_i X - X \right\|_l \}, \\ \text{Subject to} \sum_{i=1}^{k} \lambda_i = 1, \lambda_i \geq 0 \end{cases} \tag{5}$$

where $\| \ \|_l$ is a vector norm, and $l \in \{1, 2, ..., \infty\}$ .Their model could be used to solve the well-known Neysbody's problem in management science.

Multivariate Markov Chains

Multivariate Markov chains are useful in correlation analyses related to data sequences for predicting the future outcome of a random variable based on the identified correlations.
Ching and Ng (2003) applied a Multivariate Markov chain model to a multi-product demand estimation problem. Their model is expressed as

$$
\begin{cases}
X_{n+1} = \sum_{k=1}^{s} \lambda_{jk} V^{jk} X_n, \; j = 1, 2, ..., s \\
\lambda_{jk} \geq 1, 1 \leq j, k \leq s, \\
\sum_{k=1}^{s} \lambda_{jk} = 1
\end{cases}
\tag{6}
$$

In this model, the parameter λ_{jk} gives the direction and magnitude of the correlation. V^{jk} is the transition intensitiy matrix from the states in the jth sequence to the states in the kth sequence, and X_n^k is the observed state probability distribution of the kth sequence at time n.

Siu and Fung (2005) used a Multivariate Markov chain model to analyze credit rating. In matrix form, their model is given as

$$
X_{n+1} = \begin{pmatrix} X_{n+1}^1 \\ X_{n+1}^2 \\ \vdots \\ X_{n+1}^s \end{pmatrix} = \begin{pmatrix} \lambda_{11} V^{11} & \lambda_{12} V^{12} & \dots & \lambda_{1s} V^{1s} \\ \lambda_{21} V^{21} & \lambda_{22} V^{22} & \dots & \lambda_{2s} V^{2s} \\ \vdots & \vdots & \vdots & \vdots \\ \lambda_{s1} V^{s1} & \lambda_{s2} V^{s2} & \dots & \lambda_{ss} V^{ss} \end{pmatrix} \begin{pmatrix} X_n^1 \\ X_n^2 \\ \vdots \\ X_n^s \end{pmatrix},
\tag{7}
$$

where V^{jk} is the transition intensities defined as in Ching and Ng's model. Also, they proved that if the intensitiy matrix V is irreducible, the model in Equation (8) could be expressed as $\sum_{k=1}^{s} \lambda_{jk} V^{jk} X_n - X_{n+1}$. Letting Q_{jk} denote the prior transition matrix, the parameters λ_{jk} may be estimated based on the following expression:

$$
\begin{cases}
Min_{\lambda} \{Max_i \{ \left\| [\sum_{k=1}^{m} (\lambda_{jk}^1 Q_{jk} + \lambda_{jk}^2 V_{jk}) X^k - X^j] \right\|_i \} \} \\
Subject \text{ to } \sum_{k=1}^{m} (\lambda_{jk}^1 + \lambda_{jk}^2) = 1, \lambda_{jk}^1 \geq 0, \lambda_{jk}^2 \geq 0
\end{cases}
\tag{8}
$$

It is possible to combine a multivariate Markov chain with a higher-order Markov chain. As used by Ching and Ng (2004), the model considers the correlation between sequences as well as the time lags within a single data sequence.

MARKOV CHAIN MODELS

Multivariate Markov chain models have been successfully used in representing the behavior of multiple data sequences generated by the same source. Years of operation experience convinced the bank management of the importance of the correlation between retailed mortgage loans and personal credit cards, both of which are usually offered by a local bank to the same group of consumers in the area. In most cases, credit cards are used to purchase daily supplies, such as food and consumer goods. Thus, with the fluctuation of the macro-economic and employment situations, the question becomes: what is more important, house or food?

To answer this question, one needs to have information not only about the direction of the correlation, but also about its magnitude. The high-order multivariate Markov chain model introduced by Ching and NG (2006) could be a good candidate for analyzing and quantifying the correlation that has been long observed by the credit risk management personals in banking.

Table 1 defines the past due and prepayment states S_j , j = -3, -2, -1, 0, 1,2,3, as well as the default states R_k for the Markov chain model.

According to the Basel accord II, Basel Committee on Banking Supervision (1997), the definition of default is more than 90 days past due, which is represented by S_3. However, there have been cases where the obligations on a loan, which have already been more than 90 days past due, has been paid off. As a result, the definition of default is modified to be the state of default that is triggered by a permanent force, such as death or an application of chapter 7 or chapter 13 bankruptcy protections. Let R_i be the default state contributed by these permanent events and let S_{-i} be the state of a prepaid period defined as $S_{-j} = (X_i - Y_i)/Y_i$, where X_i is the actual payment at month i and Y_i is the scheduled payment at month i. One can see that state S_{-j} is defined as the extra payment over the scheduled payment, which measures how many future monthly payments have been made as a current onetime payment. It is not a precise measurement method, compared with the tools introduced by other papers in the literature, but it fits best in the context of this model.

Table 1 Definitions of the different states of the Markov chain

Past Due and Prepayment States $S_j, j = -3, -2, -1, 0, 1, 2, 3$		Default States R_k $R_k, k = 1, 2, 3, 4$	
S_{-3}	Prepaid More than 91 days	R_1	Sold by Bank
S_{-2}	Prepaid 61 days – 90 days	R_2	All others
S_{-1}	Prepaid 31 days – 60 days	R_3	Prepayment more than 50% of the remaining loan
S_0	No more than 30 days past due	R_4	Prepayment less than 50% of the remaining loan
S_1	31 days – 60 days past due		
S_2	61 days – 90 days past due		
S_3	More than 91 days past due		

Multivariate Markov Chain

Multivariate Markov chain models have many applications in multi-product demand estimation, credit rating, DNA sequence, and genetic networks. In this chapter, we will use the model proposed by Ching and Ng (2006).

$$\begin{cases} F_{n+1} = \sum_{\alpha=1}^{2} \lambda_{\alpha\beta} V^{\alpha\beta} F_n, \beta = 1,2 \\ \lambda_{\alpha\beta} \geq 1, 1 \leq \alpha, \beta \leq 2, \\ \sum_{\beta=1}^{2} \lambda_{\alpha\beta} = 1 \end{cases} \tag{9}$$

In this model, the parameter $\lambda_{\alpha\beta}$ gives the direction and magnitude of the correlation in the model outcome. We define $\alpha, \beta = 1,2$ as the data sets for retail mortgage loans and personal credit cards, respectively. $F_{n+1} = (F^{\alpha}_{n+1}, F^{\beta}_{n+1})^T$ refers to the probability distribution vector in each of the states. $F^{\alpha}_{n+1} = (F^{\alpha}_{n+1,S_i}, F^{\alpha}_{n+1,R_k})^T$ $, i = -3,-2,-1,0,1,2,3$; $k = 1,2,3,4$ at time $t = n+1$ is the probability distribution vector for the retail mortgage, while F^{β}_{n+1} is that for personal credit cards at time $t = n+1$. $V^{\alpha\beta}$ is defined as the intensity of transition between states of retail mortgage and personal credit cards. The matrix form of Equation (9) is given as

$$F_{n+1} = \begin{pmatrix} F^{\alpha}_{n+1} \\ F^{\beta}_{n+1} \end{pmatrix} = \begin{pmatrix} \lambda_{\alpha\alpha} V^{\alpha\alpha} & \lambda_{\alpha\beta} V^{\alpha\beta} \\ \lambda_{\beta\alpha} V^{\beta\alpha} & \lambda_{\beta\beta} V^{\beta\beta} \end{pmatrix} \begin{pmatrix} F^{\alpha}_{n} \\ F^{\beta}_{n} \end{pmatrix}, V^{ij} = \begin{bmatrix} I^{ij} & O^{ij} \\ R^{ij} & Q^{ij} \end{bmatrix}, i, j = \alpha, \beta \tag{10}$$

$$\text{or, } F_{n+1} = WF_n, W = \begin{pmatrix} \lambda_{\alpha\alpha} V^{\alpha\alpha} & \lambda_{\alpha\beta} V^{\alpha\beta} \\ \lambda_{\beta\alpha} V^{\beta\alpha} & \lambda_{\beta\beta} V^{\beta\beta} \end{pmatrix}$$

where, $F^{j}_{n+1} = (F_{n+1,S_i}, F_{n+1,R_k})^T, i = -2,-1,0,1,2, k = 1,2,3,4, j = \alpha, \beta$, while I^{ij}, O^{ij}, R^{ij}, Q^{ij} are given in Figure 1

Figure 1 Transition intensity matrices between retail mortgages and credit cards

$$I^{ij}{}_{4\times4}=\begin{array}{c|cccc} & R_1 & R_2 & R_3 & R_4\\ \hline R_1 & 1 & 0 & 0 & 0\\ R_2 & 0 & 1 & 0 & 0\\ R_3 & 0 & 0 & 1 & 0\\ R_4 & 0 & 0 & 0 & 1\end{array},\quad O^{ij}{}_{4\times7}=\begin{array}{c|ccccc} & S_{-2} & S_{-1} & S_0 & S_1 & S_2\\ \hline R_1 & 0 & 0 & 0 & 0 & 0\\ R_2 & 0 & 0 & 0 & 0 & 0\\ R_3 & 0 & 0 & 0 & 0 & 0\\ R_4 & 0 & 0 & 0 & 0 & 0\end{array}$$

$$R^{ij}{}_{7\times4}=\begin{array}{c|cccc} & R_1 & R_2 & R_3 & R_4\\ \hline S_{-2} & \mu_{-2,1} & \mu_{-2,2} & \mu_{-2,3} & \mu_{-2,4}\\ S_{-1} & \mu_{-1,1} & \mu_{-1,2} & \mu_{-1,3} & \mu_{-1,4}\\ S_0 & \mu_{0,1} & \mu_{0,2} & \mu_{0,3} & \mu_{0,4}\\ S_1 & \mu_{1,1} & \mu_{1,2} & \mu_{1,3} & \mu_{1,4}\\ S_2 & \mu_{2,1} & \mu_{2,2} & \mu_{2,3} & \mu_{2,4}\end{array},\quad Q^{ij}{}_{7\times7}=\begin{array}{c|ccccc} & S_{-2} & S_{-1} & S_0 & S_1 & S_2\\ \hline S_{-2} & v_{-2,-2} & v_{-2,-1} & v_{-2,0} & v_{-2,1} & 0\\ S_{-1} & v_{-1,-2} & v_{-1,-1} & v_{-1,0} & v_{-1,1} & 0\\ S_0 & v_{0,-2} & v_{0,-1} & v_{0,0} & v_{0,1} & 0\\ S_1 & v_{1,-2} & v_{1,-1} & v_{1,0} & v_{1,1} & v_{1,2}\\ S_2 & v_{2,-2} & v_{2,-1} & v_{2,0} & v_{2,1} & v_{2,2}\end{array}$$

$i, j=\alpha,\beta$

(To more efficiently present the matrices, $i=-2,...,2$ is chosen instead of $i=-3,...,3$. Further development of equations not involving matrix and empirical analysis are based on $i=-3,...,3$): $R^{ij}{}_{7\times4}, O^{ij}{}_{4\times7}$ are the transitions from transient to absorbing states and among transient states, respectively. By the definition of an absorbing state, $I^{ij}{}_{4\times4}, O^{ij}{}_{4\times7}$ are a 4×4 identity matrix and a 4×7 zero matrix, respectively.

Furthermore, letting $c_{lk}{}^{ij}, i, j=\alpha,\beta$ be the transition intensitiy between state l in data set i and state k in dataset j and $\Theta=\{R_{kl}^{\alpha\beta}, Q_{kl}^{\alpha\beta}, R_{lk}^{\beta\alpha}, Q_{lk}^{\beta\alpha}\}$, $l\in\{S_{-3},S_{-2},S_{-1}\}, k\in\{S_{-3},S_{-2},S_{-1},S_0,$ $S_1,S_2,S_3,R_1,R_2,R_3,R_4\}$, the elements of $R^{ij}{}_{7\times4}$ and $Q^{ij}{}_{7\times7}$ are calculated from the following equations:

$$C_{lk}{}^{ij}=\begin{pmatrix} c_{-3,-3}{}^{ij} & \cdots & c_{-3,4}{}^{ij}\\ \vdots & \ddots & \vdots\\ c_{4,-3}{}^{ij} & \cdots & c_{4,-3}{}^{ij}\end{pmatrix} V_{lk}{}^{ij}=\begin{pmatrix} v_{-3,-3}{}^{ij} & \cdots & v_{-3,4}{}^{ij}\\ \vdots & \ddots & \vdots\\ v_{4,-3}{}^{ij} & \cdots & v_{4,-3}{}^{ij}\end{pmatrix} \tag{11}$$

$$v_{-3,3}{}^{ij}=\begin{cases}\dfrac{c_{-3,-3}{}^{ij}}{\sum_{n=S_{-3}}^{R_4} c_{m,n}}, & \text{if } \sum_{n=S_{-3}}^{R_4} c_{m,n}\neq 0, c_{m,n}\notin\Theta\\ 0, & \text{Otherwise}\end{cases},$$

where Θ stands for a set of transitions between any states of mortgage loans and any prepaid states of credit cards.

Based on the assumptions that $V^{ij} = \begin{bmatrix} I^{ij} & O^{ij} \\ R^{ij} & Q^{ij} \end{bmatrix}, V^{ij} \notin \Theta$ is irreducible and $\lambda_{\alpha\beta} > 1$, Ching and Ng (2006) proved that there is a unique stationary vector $F = \begin{pmatrix} F^{\alpha} \\ F^{\beta} \end{pmatrix}$, such that $F = WF$, and $\sum_{i=S_{-3}}^{R_k} | F^j |_i, j = \alpha, \beta.$

According to Ching and Ng (2006), by letting $\psi = \left\| \sum_{\alpha=1}^{\beta} \lambda_{\alpha\beta} V^{\alpha\beta} F^{\beta} - F^{\alpha} \right\|_{\infty}$ be the vector norm, where ψ is defined as $\max\{\psi_{\alpha}, \psi_{\beta}\}$ by Burden and Faires (2001), the parameters of the above model could be solved by linear programming:

$$\begin{cases} Min_{\lambda}\{Max\{\sum_{\alpha=1}^{\beta} \lambda_{\alpha\beta} V^{\alpha\beta} F^{\beta} - F^{\alpha}\}\} \\ \text{subject to } \sum_{\alpha=1}^{\beta} \lambda_{\alpha\beta} = 1 \text{ and } \lambda_{\alpha\beta} \geq 0, \alpha, \beta = 1, 2 \end{cases} \tag{12}$$

In the next subsection, we will introduce a high-order Markov chain, which, under a normal macroeconomic environment, could produce more accurate results for analyzing loans payment behavior.

High-Order Markov Chain

In analysis of real-world problems like retail mortgage loans and credit cards payments, the behaviors of the payments are supposed to be affected by the prevailed macro-economic factors such as local interest rates and employment. On the other hand, past payment pattern could also play a role in the current and future payment. When this is indeed the case, a high-order Markov chain model might give a more accurate description of the real payment behavior and may offer better predictions. Ching and Ng (2004) proved that a second-order Markov chain model predicted a product's sale demand with 83% accuracy while a first-order version provided only 74% accuracy with the same data set.

Unfortunately, a kth order Markov chain with m states will have $(m-1)m^k$ model parameters, and the number of parameters (transition probabilities) will increase exponentially with an increase in the order of the model. Raftery (1985) introduced a higher-order Markov chain model with only one additional parameter for each extra lag. By assuming $Q = [q_{ij}]$ is a stationary transition matrix, the model could be written as:

$$P(X^n = j_0 \mid X^{(n-1)} = j_1, \ldots\ldots, X^{(n-k)} = j_k) = \sum_{i=1}^{k} \lambda_i v_{j_0 j_i} \tag{13}$$

where, $\sum_{i=1}^{k} \lambda_i = 1, 0 \le \sum_{i=1}^{k} \lambda_i v_{j_0 j_i} \le 1$. It could be also presented in matrix form as

$$P^{(n+k+1)} = \sum_{i=1}^{k} \lambda_i V P^{(n+k+1-i)}, \sum_{i=1}^{k} \lambda_i = 1 \tag{14}$$

where, $P^{(n+k+1)} = (P_{S_i}^{(n+k+1)})^T, i = 1, 2, .., m$ is the probability distribution of states at time $n + k + 1$. Ching and Ng (2006) generalized Raftery's model in (14) by allowing the transition matrix $V = [v_{ij}]$ to vary over lags, that is, $V_i \ne V_j, i \ne j$. Thus, the model reduces to

$$P^{(n+k+1)} = \sum_{i=1}^{k} \lambda_i V_i P^{(n+k+1-i)} \quad . \tag{15}$$

Also, Ching and Ng (2002) proved that if V_k is irreducible and $\lambda_k > 0$ such that $0 \le \lambda_k \le 1$ and $\sum_{i=1}^{k} \lambda_i = 1$, then $P^{(n+k+1)} = (P_{S_i}^{(n+k+1)})^T, i = 1, 2, .., m$ is stationary, that is

$$\begin{aligned} \lim_{n\to\infty} P^{(n+k+1)} &= \lim_{n\to\infty} \sum_{i=1}^{k} \lambda_i V_i P^{(n+k+1-i)} \\ \Rightarrow P &= \sum_{i=1}^{k} \lambda_i V_i P \\ \Rightarrow (I - \sum_{i=1}^{k} \lambda_i V_i) P &= 0 \end{aligned} \tag{16}$$

where I is an $m \times m$ identity matrix, and m is the number of transient states. One can also show that $1^T P = 1, 1^T = (1 \quad \ldots \quad 1)_{1\times m}$. Given the probability distribution matrix P and the transition intensitiy matrix V which could be observed from the data sequence and calculated from Equation (11). However, a better way to solve this linear system is to use the algorithm proposed by Ching and Ng (2006). They used a linear programming technique defined as

$$\begin{cases} Min_\lambda \{ \left\| \sum_{i=1}^{k} \lambda_i V_i P - P \right\|_l \}, \\ \text{subject to} \sum_{i=1}^{k} \lambda_i = 1, \lambda_i \ge 0 \end{cases} \tag{17}$$

where $\| \; \|_l$ is a vector norm, and $l \in \{1, 2, \infty\}$. For simplicity, we choose $l = 1$. Thus, an equivalent linear programming technique proposed by Ching and Ng (2006) is as follows:

$$Min_\lambda \sum_{l=1}^{m} w_l \text{, subject to} \tag{18}$$

$$\begin{pmatrix} w_1 \\ w_2 \\ \cdots \\ w_m \end{pmatrix} \geq X - [V_1 X \mid V_2 X \ldots \mid V_k X] \begin{pmatrix} \lambda_1 \\ \lambda_2 \\ \cdots \\ \lambda_k \end{pmatrix}$$

$$\begin{pmatrix} w_1 \\ w_2 \\ \cdots \\ w_m \end{pmatrix} \geq X + [V_1 X \mid V_2 X \ldots \mid V_k X] \begin{pmatrix} \lambda_1 \\ \lambda_2 \\ \cdots \\ \lambda_k \end{pmatrix}$$

In the application section, due to the seasonal fluctuation, we will use a fourth order Markov chain in the hope that it will result in a better representation of the loan behavior.

High-Order Multivariate Markov Chain

By assuming that the state probability distribution of the $j \cdot th$ sequence at time $t = r + 1$ depends on the state probability distribution of all sequences at times $t = r, r-1, ..., r-n+1$, Ching and Ng (2006) proposed a higher-order multivariate Markov chain model:

$$\begin{cases} F_{r+1}^{j} = \sum_{k=1}^{s} \sum_{h=1}^{n} \lambda_{jk}^{h} V_h^{jk} F_{r-h+1}^{k}, \ j = 1, 2, ..., s \\ \lambda_{jk}^{h} \geq 0, 1 \leq j, k \leq s, 1 \leq h \leq n \\ \sum_{k=1}^{s} \sum_{h=1}^{n} \lambda_{jk}^{h} = 1, \ j = 1, 2, ..., s \end{cases} \tag{19}$$

where V_h^{jk} is the $h \cdot th$ intensity transition matrix indicating the $h \cdot th$ intensity transition from states in the $j \cdot th$ sequence at time $t = r - h + 1$ to states in the $k \cdot th$ sequence at time $t = r + 1$. In fact, each V_h^{jk} is a $m \times m$ matrix represented by

$$V_h^{jk} = \begin{pmatrix} v_{-3,-3} & \cdots & v_{-3,4} \\ \vdots & \ddots & \vdots \\ v_{4,-3} & \cdots & v_{4,4} \end{pmatrix}_h^{jk}, v_{i,j} \notin \Theta \tag{20}$$

Again, $\Theta = \{R_{kl}^{\alpha\beta}, Q_{kl}^{\alpha\beta}, R_{lk}^{\beta\alpha}, Q_{lk}^{\beta\alpha}\}$, $l \in \{S_{-3}, S_{-2}, S_{-1}\}, k \in \{S_{-3}, S_{-2}, S_{-1}, S_0, S_1, S_2, S_3, R_1, R_2, R_3, R_4\}$. Detailed explanation on Θ could be found in Section 2.1. Equation (19) could also be written in matrix form:

$$\begin{aligned} F_{r+1}^{\alpha} &= B^{\alpha\alpha} F_r^{\alpha} + B^{\alpha\beta} F_r^{\beta} \\ F_{r+1}^{\beta} &= B^{\beta\alpha} F_r^{\alpha} + B^{\beta\beta} F_r^{\beta} \end{aligned} \tag{21}$$

where

$$B^{\alpha\beta} = \begin{pmatrix} \lambda_{\alpha\beta}^{4} V_4^{\alpha\beta} & \lambda_{\alpha\beta}^{3} V_3^{\alpha\beta} & \lambda_{\alpha\alpha,\beta\beta}^{2} V_2^{\alpha\beta} & \lambda_{\alpha\beta}^{1} V_1^{\alpha\beta} \\ I & 0 & 0 & 0 \\ 0 & I & 0 & 0 \\ 0 & 0 & I & 0 \end{pmatrix}_{7\cdot 4\times 7\cdot 4} \qquad \alpha \neq \beta$$

and

$$B^{\alpha\alpha,\beta\beta} = \begin{pmatrix} \lambda_{\alpha\alpha,\beta\beta}^{4} V_4^{\alpha\alpha,\beta\beta} & \lambda_{\alpha\alpha,\beta\beta}^{3} V_3^{\alpha\alpha,\beta\beta} & \lambda_{\alpha\alpha,\beta\beta}^{2} V_2^{\alpha\alpha,\beta\beta} & \lambda_{\alpha\alpha,\beta\beta}^{1} V_1^{\alpha\alpha,\beta\beta} \\ I & 0 & 0 & 0 \\ 0 & I & 0 & 0 \\ 0 & 0 & I & 0 \end{pmatrix}_{7\cdot 4\times 7\cdot 4}$$

where $F_r^{(j)} = (F_r^{(j)}, F_{r-1}^{(j)}, ..., F_{r-n+1}^{(j)})^T$, $j = 1, 2, ..., s$, and V_n^{ii}, V_n^{ij} is specified by equation (20). In our case, $s \in \{\alpha, \beta\}$. The model introduced in equation (22) is too complicated to be solved by linear programming. We will use the direct algorithm in MathCAD® to solve this model in matrix form.

APPLICATION

An Ohio local bank provided us with 18 consecutive months (from April 2005 to September 2006) of data on retail mortgage loans and credit cards. Using these data, we will apply each of the three models (namely, the multivariate model in Equation (12), the higher-order model in Equation (18), and the multivariate higher-order model in Equation (21)) to analyze the correlation between retail mortgage loans and credit cards. Also, the three models will be compared with regard to predicting the probability distribution in the next period.

Multivariate Model

One interest to a bank is the direction and magnitude of the correlation between retail mortgage and credit card because, normally, these services are taken by the same group of people in a local area. Macroeconomic factors could be common drivers that have effects on payment patterns and behaviors of both retail mortgage and credit card. In this analysis, α, β refer to the retail mortgage and credit cards dataset, respectively. Following the definition in Table 1, there are 7 transient states and 4 absorbing states which are represented as $i, k \in \{S_i, R_k\} i = -3, \; -2, -1, 0, 1, 2, 3; k = 1, 2, 3, 4$. Different lags or orders will be referred to as $j \in \{1, 2, 3, 4\}$. For example, when j = 4, the transition intensity matrix:

$V_4^{\alpha\beta} = \begin{pmatrix} v_{-3,-3} & \cdots & v_{-3,4} \\ \vdots & \ddots & \vdots \\ v_{4,-3} & \cdots & v_{4,-3} \end{pmatrix}_4^{\alpha\beta}$ refers to a 4-month lagged transition from retail mortgage states to credit card states. Thus, the multivariate Markov model proposed by Ching and Ng (2006) is given as $F = \begin{pmatrix} \lambda_{\alpha\alpha} V^{\alpha\alpha} & \lambda_{\alpha\beta} V^{\alpha\beta} \\ \lambda_{\beta\alpha} V^{\beta\alpha} & \lambda_{\beta\beta} V^{\beta\beta} \end{pmatrix} F$, where $F = \begin{pmatrix} F^{\alpha} \\ F^{\beta} \end{pmatrix}$, which could also be written as $\sum_{\alpha=1}^{\beta} \lambda_{\alpha\beta} V^{\alpha\beta} F^{\beta} = F^{\alpha} \Rightarrow \sum_{\alpha=1}^{\beta} \lambda_{\alpha\beta} V^{\alpha\beta} F^{\beta} - F^{\alpha} = 0$

The sign and values of the parameters $\lambda = \{\lambda^{\alpha\alpha}, \lambda^{\alpha\beta}, \lambda^{\beta\alpha}, \lambda^{\beta\beta}\}$ provide the direction and the magnitude of the correlation. Also, given the probability distribution at time t, the model can predict the distribution at time $t+1$. For simplicity, we choose $l = 1$ in the vector norm $\|\cdot\|_l$. Thus, the linear programming in Equation (12) becomes

$$Min_{\lambda} \{ \sum_{\alpha=1}^{\beta} \lambda_{\alpha\beta} V^{\alpha\beta} F^{\beta} - F^{\alpha} \} \tag{22}$$

$$\text{subject to } \sum_{\alpha=1}^{\beta} \lambda_{\alpha\beta} = 1 \text{ and } \lambda_{\alpha\beta} \geq 0, \alpha, \beta = 1, 2$$

We will provide methods for solving the parameter $\lambda = \{\lambda^{\alpha\alpha}, \lambda^{\alpha\beta}, \lambda^{\beta\alpha}, \lambda^{\beta\beta}\}$ by the *Minerr()* method of MathCAD and the *Solver()* function of Microsoft Excel. The models are built based on the datasets 1 – 15 periods. The last period (period 16) is used to check on and compare model performances.

The transition intensity matrix for credit cards as computed from Equation (11) is

Figure 2(A) Transition intensitiy matrix within credit cards

$$V^{\alpha\alpha} = \begin{array}{c} \\ R_1 \\ R_2 \\ R_3 \\ R_4 \\ S_{-3} \\ S_{-2} \\ S_{-1} \\ S_0 \\ S_1 \\ S_2 \\ S_3 \end{array} \begin{array}{c} \begin{array}{ccccccccccc} R_1 & R_2 & R_3 & R_4 & S_{-3} & S_{-2} & S_{-1} & S_0 & S_1 & S_2 & S_3 \end{array} \\ \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0.0014 & 0.0005 & 0 & 0.0012 \\ 0.0214 & 0 & 0.0012 & 0 & 0 & 0 & 0.0014 & 0.9514 & 0.0345 & 0 & 0.0011 \\ 0.0104 & 0.0014 & 0.0021 & 0.0045 & 0 & 0.0005 & 0.0021 & 0.0285 & 0.0014 & 0.9124 & 0.0024 \\ 0.0124 & 0.0072 & 0.0017 & 0.1040 & 0 & 0 & 0 & 0.0012 & 0.0041 & 0.0741 & 0.0076 \\ 0.0001 & 0.0017 & 0.0065 & 0.0032 & 0 & 0.0012 & 0 & 0.0034 & 0 & 0.0018 & 0.0015 \end{bmatrix} \end{array}$$

Also, the transition intensitiy matrix between credit card and retail mortgage is

Figure 2(B) Transition intensitiy matrix between retail mortgages and credit cards

$$
V^{\alpha\beta} = \begin{array}{c} \\ R^{\alpha}_{1} \\ R^{\alpha}_{2} \\ R^{\alpha}_{3} \\ R^{\alpha}_{4} \\ S^{\alpha}_{-3} \\ S^{\alpha}_{-2} \\ S^{\alpha}_{-1} \\ S^{\alpha}_{0} \\ S^{\alpha}_{1} \\ S^{\alpha}_{2} \\ S^{\alpha}_{3} \end{array}
\begin{array}{c}
\begin{array}{ccccccccccc} R^{\beta}_{1} & R^{\beta}_{2} & R^{\beta}_{3} & R^{\beta}_{4} & S^{\beta}_{-3} & S^{\beta}_{-2} & S^{\beta}_{-1} & S^{\beta}_{0} & S^{\beta}_{1} & S^{\beta}_{2} & S^{\beta}_{3} \end{array} \\
\begin{bmatrix}
0.5901 & 0 & 0.1478 & 0.0471 & 0 & 0 & 0 & 0 & 0.0014 & 0.0011 & 0.0001 \\
0.0012 & 0.4748 & 0.1478 & 0.0014 & 0 & 0 & 0 & 0.0031 & 0.0784 & 0.0145 & 0.0984 \\
0.0651 & 0.1245 & 0.5684 & 0.0145 & 0 & 0 & 0 & 0.0214 & 0.0321 & 0.0141 & 0.0148 \\
0.0914 & 0 & 0.1024 & 0.4512 & 0 & 0 & 0 & 0 & 0 & 0.2147 & 0.1473 \\
0 & 0.2541 & 0 & 0.0142 & 0 & 0 & 0 & 0.2415 & 0.0012 & 0.1457 & 0.0007 \\
0.0012 & 0 & 0.0014 & 0.0661 & 0 & 0 & 0 & 0.1454 & 0.0047 & 0.0018 & 0.0009 \\
0.0019 & 0 & 0 & 0.0008 & 0 & 0 & 0 & 0.0594 & 0.0124 & 0.0142 & 0.0005 \\
0.0001 & 0 & 0.0014 & 0 & 0 & 0 & 0 & 0.1484 & 0.0978 & 0.0014 & 0.0078 \\
0.1025 & 0 & 0 & 0.0874 & 0 & 0 & 0 & 0.1487 & 0.3412 & 0.0002 & 0.4816 \\
0.0021 & 0.1721 & 0.2365 & 0 & 0 & 0 & 0 & 0.1475 & 0.3874 & 0.2314 & 0.1673 \\
0 & 0.6748 & 0.0002 & 0 & 0 & 0 & 0 & 0.0987 & 0.1114 & 0.1387 & 0.1991
\end{bmatrix}
\end{array}
$$

Note that the transition intensities in $V^{\alpha\beta}$ between states $R_k, k = 1,2,3,4$ and between $S_i, i = -3,-2,-1,0,1,2,3$ are no longer necessarily 1 and 0 because the charge-off in a retail mortgage loan does not always transit to the charge-off of credit cards and vice verse.

The calculation of its elements is given as

$$
v_{ij}^{*} = \frac{\sum_{t=1}^{15} c_{ijt}}{\left.\sum_{j=-3}^{k=4} \sum_{t=1}^{15} c_{ijt}\right._{i}}, i = -3,-2,-1,-,1,2,3, i \neq j, k = 1,2,3,4, * \in \{\alpha, \beta\}, v^{*} \notin \Theta \qquad (23)
$$

where c_{ijt} is the observed frequency count of the transition between states at time t. Furthermore, the probability distribution vectors in each of the states are given as

$$
F = \begin{pmatrix} F^{\alpha} \\ F^{\beta} \end{pmatrix}
$$

Figure 3 Probability distribution vectors

$$
\begin{aligned}
F_{\alpha} &= (0.0131 \quad 0.0286 \quad 0.1025 \quad 0.7523 \quad 0.0246 \quad 0.0321 \quad 0.0125 \quad 0.0098 \quad 0.0078 \quad 0.0115 \quad 0.0051)^{T} \\
F_{\beta} &= (0.0000 \quad 0.0000 \quad 0.0001 \quad 0.7958 \quad 0.0212 \quad 0.0565 \quad 0.0814 \quad 0.0165 \quad 0.0158 \quad 0.0107 \quad 0.0014)^{T}
\end{aligned}
$$

Thus, the model in Equation (13) solved by the *Minerr()* method of MathCAD is given as

$$F_{n+1}^{\alpha} = 0.2955V^{\alpha\alpha}F_n^{\alpha} + 0.7045V^{\alpha\beta}F_n^{\beta} \qquad (24)$$
$$F_{n+1}^{\beta} = 0.6077V^{\beta\alpha}F_n^{\alpha} + 0.3923V^{\beta\beta}F_n^{\beta}$$

where, $\lambda = \{\lambda^{\alpha\alpha}, \lambda^{\alpha\beta}, \lambda^{\beta\alpha}, \lambda^{\beta\beta}\} = \{0.2955, 0.7045, 0.6077, 0.3923\} and \sum_{\beta} \lambda^{\alpha\beta} = 1$

From the elements of the vector λ, it is seen that there is a relatively strong positive correlation between retail mortgage and credit cards payment. Also, the correlation is not symmetric ($\lambda_{\alpha\beta} = 0.7045 \neq 0.6077 = \lambda_{\alpha\beta}$). This result could be explained by the payment sequence for each month's bills, or the inelasticity of the mortgage payments. On the other hand, the function of credit cards could be easily replaced by cash or other payment method.

Higher-Order Model

In this subsection, we will apply a 4^{th}-order Markov chains model to predict the probability distribution between states defined in Table 1. Data for this model are provided by the same Ohio local bank. The parameters in the model of Equation (15) provide information about the correlation between states of different lags. This correlation will reveal which lag has most influence over current states. That is, by taking the past several transitions into consideration, we hope the model will offer better predictions.

From Equation (16), $P^{(n+k+1)} = \sum_{i=1}^{k} \lambda_i V P^{(n+k+1-i)}; \sum_{i=1}^{k} \lambda_i = 1$. $V = (V^t)$, $t = 1, 2, 3, 4$ are the transition matrices from time $n - t$ to n where n refers to the current time.

From Equation (11) one can calculate the probability matrix $V = (V^t), t = 1, 2, 3, 4$, the elements of which represent the transition between states at time $n - t$ to states at time n. The probability matrix V^2 gives the transition between states two months ago and the current states. The transition intensity matrix between two-month-lags is given in Figure 4:

Figure 4 Transition intensity matrix between two-month-lags

$$\begin{array}{cc}
 & \begin{array}{ccccccccccc} R^0{}_1 & R^0{}_2 & R^0{}_3 & R^0{}_4 & S^0{}_{-3} & S^0{}_{-2} & S^0{}_{-1} & S^0{}_0 & S^0{}_1 & S^0{}_2 & S^0{}_3 \end{array} \\
(V^{\alpha\alpha})^2 = \begin{array}{c} R^2{}_1 \\ R^2{}_2 \\ R^2{}_3 \\ R^2{}_4 \\ S^2{}_{-3} \\ S^2{}_{-2} \\ S^2{}_{-1} \\ S^2{}_0 \\ S^2{}_1 \\ S^2{}_2 \\ S^2{}_3 \end{array} &
\begin{bmatrix}
1 & 0. & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0.0114 & 0 & 0 & 0 & 0.0145 & 0.2354 & 0 & 0.6874 & 0 & 0 & 0 \\
0 & 0 & 0.0142 & 0.0024 & 0 & 0 & 0.4571 & 0.1023 & 0.0100 & 0 & 0 \\
0 & 0 & 0 & 0 & 0.0001 & 0.0089 & 0.2001 & 0.4517 & 0.0045 & 0.0002 & 0 \\
0.0001 & 0 & 0.0541 & 0 & 0.0003 & 0.0313 & 0.0065 & 0.7942 & 0.0504 & 0.0314 & 0.0055 \\
0.0894 & 0 & 0 & 0 & 0 & 0 & 0 & 0.1247 & 0.4872 & 0.1245 & 0.4011 \\
0.1021 & 0.1721 & 0 & 0 & 0 & 0 & 0 & 0.1148 & 0.3247 & 0.1055 & 0.5478 \\
0.1011 & 0 & 0.0048 & 0 & 0 & 0 & 0 & 0 & 0.0033 & 0.1387 & 0.7245
\end{bmatrix}
\end{array}$$

If n is the number of available monthly data, one has $Mod(\frac{n-1}{t})$ of transition matrices between time $n-t$ and time n. Matrix V^2 represents the average over the corresponding elements of the transition matrices. By the same token, we used only 15 time periods to build the model. Data in the last period were used to test the performance of the model. The probability distribution vector was estimated to be

Figure 5. Probability distribution vector

$$F = (0.0131 \quad 0.0286 \quad 0.1025 \quad 0.7523 \quad 0.0246 \quad 0.0321 \quad 0.0125 \quad 0.0098 \quad 0.0078 \quad 0.0115 \quad 0.0051)^T$$

Thus, by the linear programming of Equation (21), one has the following scheme given in Figure 6:

Figure 6 Linear programming scheme

$$V^1F = (0.0002, 0.0124, 0.1554, 0.0147, 0.7146, 0.0078, 0.0065, 0.0512, 0.0547, 0.0101, 0.0187)^T$$
$$V^2F = (0.0131, 0.0026, 0.1025, 0.7523, 0.0146, 0.0100, 0.0072, 0.0148, 0.0083, 0.0128, 0.0056)^T$$
$$V^3F = (0.0125, 0.0457, 0.1712, 0.0145, 0.0897, 0.4571, 0.2578, 0.0547, 0.0345, 0.0777, 0.1463)^T$$
$$V^4F = (0.0784, 0.0124, 0.1574, 0.1244, 0.1278, 0.4587, 0.2144, 0.2874, 0.0013, 0.0784, 0.0659)^T$$
$$Min_{\lambda_1,\lambda_2,\lambda_3,\lambda_4}(w_1 + w_2 + w_3 + w_4 + w_5 + w_6 + w_7)$$

Subject to:

$$\begin{cases} w_1 \geq 0.0131 - 0.0002\lambda_1 - 0.0131\lambda_2 - 0.0125\lambda_3 - 0.0784\lambda_4 \\ w_2 \geq 0.0286 - 0.0124\lambda_1 - 0.0026\lambda_2 - 0.0457\lambda_3 - 0.0124\lambda_4 \\ w_3 \geq 0.1025 - 0.1554\lambda_1 - 0.1025\lambda_2 - 0.1712\lambda_3 - 0.1574\lambda_4 \\ w_4 \geq 0.7523 - 0.0147\lambda_1 - 0.7523\lambda_2 - 0.0145\lambda_3 - 0.1244\lambda_4 \\ w_5 \geq 0.0246 - 0.7146\lambda_1 - 0.0146\lambda_2 - 0.0897\lambda_3 - 0.1278\lambda_4 \\ w_6 \geq 0.0321 - 0.0078\lambda_1 - 0.0100\lambda_2 - 0.4571\lambda_3 - 0.4587\lambda_4 \\ w_7 \geq 0.0125 - 0.0065\lambda_1 - 0.0072\lambda_2 - 0.2578\lambda_3 - 0.2144\lambda_4 \\ w_8 \geq 0.0098 - 0.0512\lambda_1 - 0.0148\lambda_2 - 0.0547\lambda_3 - 0.2874\lambda_4 \\ w_9 \geq 0.0078 - 0.0547\lambda_1 - 0.0083\lambda_2 - 0.0345\lambda_3 - 0.0013\lambda_4 \\ w_{10} \geq 0.0115 - 0.0101\lambda_1 - 0.0128\lambda_2 - 0.0777\lambda_3 - 0.0784\lambda_4 \\ w_{11} \geq 0.0051 - 0.0187\lambda_1 - 0.0056\lambda_2 - 0.1463\lambda_3 - 0.0659\lambda_4 \\ w_1 \geq -0.0131 + 0.0002\lambda_1 + 0.0131\lambda_2 + 0.0125\lambda_3 + 0.0784\lambda_4 \\ w_2 \geq -0.0286 + 0.0124\lambda_1 + 0.0026\lambda_2 + 0.0457\lambda_3 + 0.0124\lambda_4 \\ w_3 \geq -0.1025 + 0.1554\lambda_1 + 0.1025\lambda_2 + 0.1712\lambda_3 + 0.1574\lambda_4 \\ w_4 \geq -0.7523 + 0.0147\lambda_1 + 0.7523\lambda_2 + 0.0145\lambda_3 + 0.1244\lambda_4 \\ w_5 \geq -0.0246 + 0.7146\lambda_1 + 0.0146\lambda_2 + 0.0897\lambda_3 + 0.1278\lambda_4 \\ w_6 \geq -0.0321 + 0.0078\lambda_1 + 0.0100\lambda_2 + 0.4571\lambda_3 + 0.4587\lambda_4 \\ w_7 \geq -0.0125 + 0.0065\lambda_1 + 0.0072\lambda_2 + 0.2578\lambda_3 + 0.2144\lambda_4 \\ w_8 \geq -0.0098 + 0.0512\lambda_1 + 0.0148\lambda_2 + 0.0547\lambda_3 + 0.2874\lambda_4 \\ w_9 \geq -0.0078 + 0.0547\lambda_1 + 0.0083\lambda_2 + 0.0345\lambda_3 + 0.0013\lambda_4 \\ w_{10} \geq -0.0115 + 0.0101\lambda_1 + 0.0128\lambda_2 + 0.0777\lambda_3 + 0.0784\lambda_4 \\ w_{11} \geq -0.0051 + 0.0187\lambda_1 + 0.0056\lambda_2 + 0.1463\lambda_3 + 0.0659\lambda_4 \\ w_1, w_2, w_3, w_4, w_5, w_6, w_7, w_8, w_9, w_{10}, w_{11} \geq 0, \\ \lambda_1 + \lambda_2 + \lambda_3 + \lambda_4 = 1, \lambda_1, \lambda_2, \lambda_3, \lambda_4 \geq 0 \end{cases}$$

Applying the above scheme to the Excel *Solver(),* the parameters and the higher-order Markov chain model were estimated to give

$$\lambda = (\lambda_1, \lambda_2, \lambda_3, \lambda_4) = (0.6387, 0.2356, 0.1023, 0.0234), \sum_{i=1}^{4} \lambda_i = 1 \tag{25}$$

$$F^n = 0.6387V^1F^{n-1} + 0.2356V^2F^{n-2} + 0.1023V^3F^{n-3} + 0.0234V^4F^{n-4},$$

where $V^t, t = 1, 2, 3, 4$ is given in Figure 4, and F^{n-t} is the probability distribution observed at time lag t.

Higher-Order Multivariate Model

Before the model is applied, one needs to clarify the transition intensities. Consider two data sequences, retail mortgages $\alpha_t, t = 1, 2, ..., 16$ and credit cards $\beta_t, t = 1, 2, ..., 16$. The transition patterns are given in Figure 7:

Figure 7 Example of a high-order multivariate transition

t: 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16

$$\alpha : \alpha_1, \alpha_2, \alpha_3, \alpha_4, \alpha_5, \alpha_6, \alpha_7, \alpha_8, \alpha_9, \alpha_{10}, \alpha_{11}, \alpha_{12}, \alpha_{13}, \alpha_{14}, \alpha_{15}, \alpha_{16}$$

$$\beta : \beta_1, \beta_2, \beta_3, \beta_4, \beta_5, \beta_6, \beta_7, \beta_8, \beta_9, \beta_{10}, \beta_{11}, \beta_{12}, \beta_{13}, \beta_{14}, \beta_{15}, \beta_{16}$$

(1) Multivariate transition: $V^{\alpha\beta}, V^{\beta\alpha}$

(2) Higher-Order transition: $V_t, t = 1, 2, 3, 4$

(3) Higher-Order Multivariate transition: $V_t^{\alpha\beta}, V_t^{\beta\alpha} t = 1, 2, 3, 4$

$\alpha_t, \beta_t \in \{S_i, R_k\}, i = -3, -2, -1, 0, 1, 2, 3, k = 1, 2, 3, 4, t = 1, 2, 3, 4$

In this subsection, the model will be used to analyze the correlation between retail mortgage loans and consumer credit cards and to predict the probability distribution in the next period. Again, the data, provided by the Ohio local bank, will be used up to the first 15 periods. The last period (period 16) will be used to compare and test the models.

Based on the example in Figure 6, we define the transition intensitiy with $t = 1, 2, 3, 4$ time lags between states in retail mortgages α and credit cards β as $V_t^{\alpha\beta}, V_t^{\beta\alpha} t = 1, 2, 3, 4$. We let $V_t^{\alpha\alpha}, V_t^{\beta\beta} t = 1, 2, 3, 4$ be the higher-order transitions within retail mortgages and credit cards, respectively. As a result, there is a total of $4 \times 4 = 16$ transition intensitiy matrices. In Figure 8, we present $V_3^{\alpha\beta}$, the transition from retail mortgages states to credit cards states with time lag equal to 3.

Figure 8 $V_3^{\alpha\beta}$ is the higher—order inter transition intensity matrix

$$
\begin{array}{rc}
 & \begin{array}{ccccccccccc} R_1 & R_2 & R_3 & R_4 & S_{-3} & S_{-2} & S_{-1} & S_0 & S_1 & S_2 & S_3 \end{array} \\
V_3^{\alpha\beta} = \begin{array}{c} R_1 \\ R_2 \\ R_3 \\ R_4 \\ S_{-3} \\ S_{-2} \\ S_{-1} \\ S_0 \\ S_1 \\ S_2 \\ S_3 \end{array} &
\begin{bmatrix}
0 & 0. & 0.0014 & 0 & 0 & 0 & 0 & 0.0124 & 0.4514 & 0.0014 & 0.4012 \\
0 & 0.1922 & 0 & 0.1475 & 0 & 0 & 0.0001 & 0 & 0.0045 & 0.0145 & 0.6214 \\
0 & 0 & 0.7812 & 0 & 0 & 0 & 0 & 0.0004 & 0.0056 & 0.0014 & 0.1024 \\
0.5214 & 0 & 0.0001 & 0 & 0 & 0.0001 & 0 & 0.0047 & 0.0789 & 0.1247 & 0.1245 \\
0.0002 & 0 & 0 & 0 & 0.0011 & 0 & 0.0072 & 0.0105 & 0.0078 & 0 & 0 \\
0 & 0 & 0 & 0.0034 & 0 & 0 & 0.0087 & 0.2347 & 0.0149 & 0.0021 & 0 \\
0 & 0 & 0.0002 & 0.0005 & 0 & 0.0004 & 0.0045 & 0.1247 & 0.0524 & 0.0007 & 0 \\
0.0005 & 0 & 0.0457 & 0 & 0.0087 & 0 & 0.0032 & 0.9045 & 0.0124 & 0.0241 & 0.0001 \\
0.0547 & 0 & 0 & 0.0002 & 0 & 0 & 0.0087 & 0.0657 & 0.3578 & 0.1187 & 0.3454 \\
0.2014 & 0.0009 & 0 & 0.0065 & 0 & 0 & 0 & 0.0032 & 0.1008 & 0.0008 & 0.6111 \\
0.1024 & 0 & 0.0007 & 0.1125 & 0 & 0 & 0 & 0 & 0.0148 & 0 & 0.5487
\end{bmatrix}_3^{\alpha\beta}
\end{array}
$$

Estimates of the elements of the above matrix were obtained from Equation (11).

The model in Equation (21) is too difficult to solve by linear programming. Therefore, the MathCAD's *Minerr()* method was used to solve this problem. Due to the MathCAD's maximum limit of the elements a matrix could have, one needs to decompose the model in Equation (21) into a smaller systems of linear equations:

$$
\begin{aligned}
F_1^{\alpha} &= \lambda_{\alpha\alpha}^{1} V_1^{\alpha\alpha} F_1^{\alpha} + \lambda_{\alpha\alpha}^{2} V_2^{\alpha\alpha} F_2^{\alpha} + \lambda_{\alpha\alpha}^{3} V_3^{\alpha\alpha} F_3^{\alpha} + \lambda_{\alpha\alpha}^{4} V_4^{\alpha\alpha} F_4^{\alpha} \\
&\quad + \lambda_{\alpha\beta}^{1} V_1^{\alpha\beta} F_1^{\beta} + \lambda_{\alpha\beta}^{2} V_2^{\alpha\beta} F_2^{\beta} + \lambda_{\alpha\beta}^{3} V_3^{\alpha\beta} F_3^{\beta} + \lambda_{\alpha\beta}^{4} V_4^{\alpha\beta} F_4^{\beta} \\
F_1^{\beta} &= \lambda_{\beta\beta}^{1} V_1^{\beta\beta} F_1^{\alpha} + \lambda_{\beta\beta}^{2} V_2^{\beta\beta} F_2^{\alpha} + \lambda_{\beta\beta}^{3} V_3^{\beta\beta} F_3^{\alpha} + \lambda_{\beta\beta}^{4} V_4^{\beta\beta} F_4^{\alpha} \\
&\quad + \lambda_{\beta\alpha}^{1} V_1^{\beta\alpha} F_1^{\beta} + \lambda_{\beta\alpha}^{2} V_2^{\beta\alpha} F_2^{\beta} + \lambda_{\beta\alpha}^{3} V_3^{\beta\alpha} F_3^{\beta} + \lambda_{\beta\alpha}^{4} V_4^{\beta\alpha} F_4^{\beta}
\end{aligned} \tag{26}
$$

where $V \in (V_t^{\alpha\alpha}, V_t^{\alpha\beta}, V_t^{\beta\alpha}, V_t^{\beta\beta}), t = 1,2,3,4, \sum_{\alpha,\beta}\sum_{t=1}^{4} V_t^{\alpha\beta} = 1$ are the 11 by 11 transition matrices given by Figure 8, and $F_t^{\alpha,\beta}, t = 1,2,3,4$ are the 4 consecutive observed probability distribution vector of retail mortgages and credit cards.

From the MathCAD analysis, we obtained the following equations:

$$\begin{aligned}
\lambda &= (\lambda_{\alpha\alpha}^1, \lambda_{\alpha\alpha}^2, \lambda_{\alpha\alpha}^3, \lambda_{\alpha\alpha}^4, \lambda_{\alpha\beta}^1, \lambda_{\alpha\beta}^2, \lambda_{\alpha\beta}^3, \lambda_{\alpha\beta}^4, \lambda_{\beta\beta}^1, \lambda_{\beta\beta}^2, \lambda_{\beta\beta}^3, \lambda_{\beta\beta}^4, \lambda_{\beta\alpha}^1, \lambda_{\beta\alpha}^2, \lambda_{\beta\alpha}^3, \lambda_{\beta\alpha}^4)^T \\
&= (0.1278, 0.0914, 0.0311, 0.0154, 0.3209, 0.2365, 0.1398, 0.0371, \\
&\quad 0.2355, 0.1165, 0.0977, 0.0211, 0.0098, 0.3871, 0.0403, 0.0920)^T \\
F_{1,t+1}^{\alpha} &= 0.1278 V_1^{\alpha\alpha} F_{1,t}^{\alpha} + 0.0914 V_2^{\alpha\alpha} F_{2,t}^{\alpha} + 0.0311 V_3^{\alpha\alpha} F_{3,t}^{\alpha} + 0.0154 V_4^{\alpha\alpha} F_{4,t}^{\alpha} \\
&\quad + 0.3209 V_1^{\alpha\beta} F_{1,t}^{\beta} + 0.2365 V_2^{\alpha\beta} F_{2,t}^{\beta} + 0.1398 V_3^{\alpha\beta} F_{3,t}^{\beta} + 0.0371 V_4^{\alpha\beta} F_{4,t}^{\beta} \\
F_{1,t+1}^{\beta} &= 0.2355 V_1^{\beta\beta} F_{1,t}^{\alpha} + 0.1165 V_2^{\beta\beta} F_{2,t}^{\alpha} + 0.0977 V_3^{\beta\beta} F_{3,t}^{\alpha} + 0.0211 V_4^{\beta\beta} F_{4,t}^{\alpha} \\
&\quad + 0.0098 V_1^{\beta\alpha} F_{1,t}^{\beta} + 0.3871 V_2^{\beta\alpha} F_{2,t}^{\beta} + 0.0403 V_3^{\beta\alpha} F_{3,t}^{\beta} + 0.0920 V_4^{\beta\alpha} F_{4,t}^{\beta}
\end{aligned} \tag{27}$$

Here, $\sum_{\alpha,\beta}\sum_{t=1}^{4} V_t^{\alpha\beta} = 1$. As we can see from the parameters, the correlations within Mortgages are less significant than those within credit cards, while the correlations between retails and cards are not symmetric as confirmed by the first-order multivariate model in subsection 2.1. In subsection 3.4, the performance of this model is compared with the other two models in the previous subsections.

Comparisons among the Three Models

For the multivariate model, the data set observed in periods 1-15 (Figure 3) was used. For the higher-order univariate model, the data set with observation over 4 consecutive months (Figure 5) was required. The needed dataset is more complicated for the high-order multivariate model represented in Figure 9:

Figure 9 Probability distributions for the high-order multivariate model

$$F = \begin{pmatrix} F_t^{\alpha} \\ F_t^{\beta} \end{pmatrix}$$

$$F_t^{\alpha} = (F_{1,t}^{\alpha}, F_{2,t}^{\alpha}, F_{3,t}^{\alpha}, F_{4,t}^{\alpha})^T$$

$$F_t^{\beta} = (F_{1,t}^{\beta}, F_{2,t}^{\beta}, F_{3,t}^{\beta}, F_{4,t}^{\beta})^T$$

The Criterion used for measuring the prediction error was the normalized error:

$$E_{S_i} = \left| \frac{F_{S_i,16} - \hat{F}_{S_i}}{F_{S_i,16}} \right|, E_R = \frac{\left| \sum_{k=1}^{4} F_{R_k,16} - \hat{F}_{R_k} \right|}{\sum_{k=1}^{4} F_{R_k,16}} \tag{28}$$

$$i = -3, -2, -1, 0, 1, 2, 3, k = 1, 2, 3, 4$$

where E_{S_i} and E_{R_k} are the normalized errors for transient state S_i and absorbing states R_k, respectively. $F_{S_i,16}$ is the observed probability distribution of transient states at period 16, while $\hat{F}_{S_i}$ is the predicted probability distribution for the same states. Similary for $F_{R_k,16}$ and $\hat{F}_{R_k}$.

For predictions of transient states, the normalized errors are calculated individually, while the normalized error for absorbing states are measured as a whole because the different types of charge-off are sometimes at the discretion of the bank management. Equation (29) gives the percentage of errors in the observed dataset. Small normalized errors are expected for good model performance. Comparisons of prediction errors among the three models are presented in Table 2.

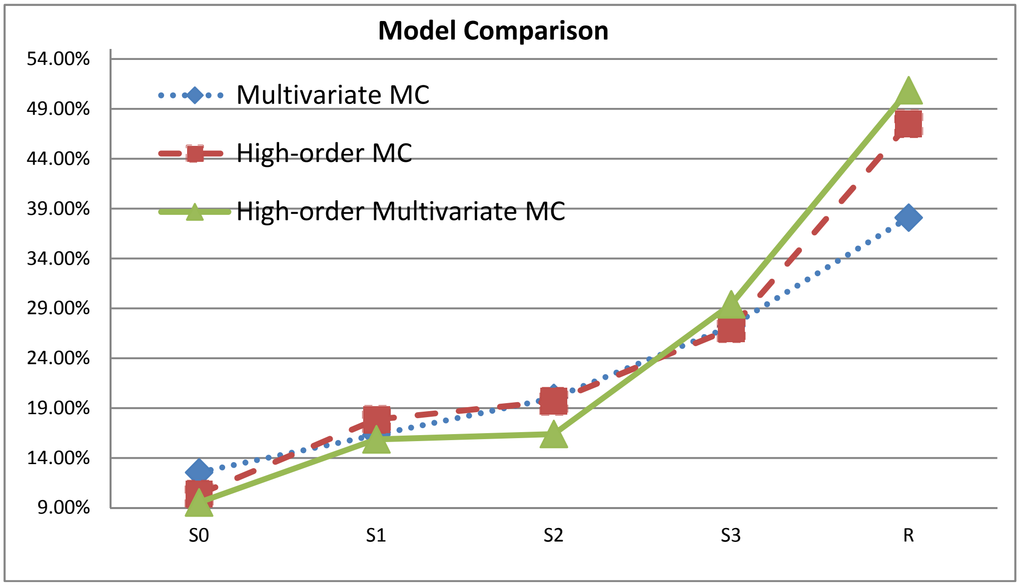
Table 2 Comparisons of prediction errors in percent among the three models, multivariate Markov chain (model (1), high-order Markov chain (model (2)), and high-order multivariate Markov chain (model(3)).

	S_{-3}	S_{-2}	S_{-1}	S_0	S_1	S_2	S_3	$\sum_{k=1}^{4} R_k$
Model (1)				12.55%	16.32%	20.02%	27.21%	38.09%
Model (2)	22.98%	36.98%	21.77%	10.37%	17.87%	19.68%	26.97%	47.51%
Model (3)				9.54%	15.87%	16.40%	29.41%	50.87%

It is seen that model (3) is more accurate in the normal state, S_0, and is better than the other two models for most other transient states. Not surprisingly, the best model to predict the absorbing states is simply the higher-order model. This result could be due to the fact that the charge-off decisions for retail mortgages have been made independently of the decisions for credit cards. This result is crucial information for the credit asset management. In other words, the bank management failed to take this correlation information into account when they made the charge-off decisions. By charge-off decisions, we mean that the bank took one of the approaches in Table 1 to charge the assets off from the system. Model (2) seems to be slightly better than model (1) in the transient states, but the differences between the two model are not substantial.

Also, the Data in Table 2 are partially presented in Figure 10.

Figure 10 Model comparisons



CONCLUSION

In this study, a higher-order multivariate Markov chain model has been used to predict mortgage loan health distribution by analyzing the delayed cross-products transition process. Furthermore, comparisons among a higher-order multivariate Markov chain model, a higher-order Markov chain model, and a multivariate Markov chain model has also been performed in order to select the best model for a particular mortgage state. We found that higher-order models give more accurate prediction if it is applied to states close to the normal state. On the contrary, for the absorbing state and the charged-off state, a simple multivariate model is preferred. On the other hand, prediction accuracy for any state in the case of the simple higher-order model falls between the other two models. As a result, the models could be used by the risk professionals and researcher as follows: if the purpose is to predict the loan's distribution, a higher-order multivariate model is preferred. On the other hand, if the purpose is to predict how many loans would be charged-off, a simple multivariate model might give you best results. Finally, simple higher-order models should be used with caution for either purpose.

The proposed models offer the bank management quantitative methods to analyze and predict its loans' behaviors. Also, this modeling approach could help the bank management in making strategic financial decisions. Furthermore, the measurement of correlation using a high-order multivariate Markov chain model offers a reliable method to analyze data for small-tomedium size local commercial banks, which, in most cases, do not have adequate resources for implementing comprehensive large computation systems.

Future research includes: 1. Analysis of the transition process under stressed macro environments using non-stationary Markov chains and stress testing; 2. Hidden Markov chains used to analyze the underling forces affecting the transition; 3. A stable transition analysis evaluation under the Basel Accord II framework.

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AN EMPIRICAL ANALYSIS ON BOARD MONITORING ROLE AND LOAN PORTFOLIO QUALITY IN BANKS

Valeria Stefanelli, Telematic University of Rome "Niccolò Cusano"
Matteo Cotugno, University of Catania

ABSTRACT

This paper aims to analyze the effectiveness of the board monitoring role on specific loan portfolio quality measures in banks (default rate, recovery rate and provisioning rate). We use a sample comprises a totality of Italian-based banks, listed at Borsa Italiana SpA in 2006-2008, and a number of accounting proxies to express the loan portfolio quality of a bank.

The results of the analysis show an overall weakness of the board role (expressed by Independents and Audit Committee on board) in monitoring loan portfolio quality of the bank, with the subsequent damage of the interests of stakeholders.

A positive contribution of board monitoring, even if partial, is highlighted in two cases: Independents seems improve recovery rate, while the Audit committee enhances provisioning rate in banks. With reference to default rate, a total negative effect of board monitoring is reported. On the base of these results, some managerial implications are proposed.

INTRODUCTION[1]

This paper aims to analyze the effectiveness of the board monitoring role on loan portfolio quality in banks. Inadequately monitored credit risk in a bank can yield into the unexpected customer downgrading, credit mispricing, higher capital requirements and, in the worst cases, economic and social losses extending to the bank's stakeholders (shareholders, regulators, customers, institutional investors, etc.).

The board of directors is ultimately responsible for the bank; especially in the banking business, the board has a fiduciary role, in which the responsibility of its supervisory and monitoring the managerial decision-making processes goes beyond the interests of the shareholders, to encompass those of all its stakeholders (Mottura, 1998; Adams & Mehran, 2003; Macey & O'Hara, 2003; Levine, 2004) and, ultimately, the economic system as a whole, if we take into account the role played by credit intermediaries in the economic development of countries (de Andres & Vallelado, 2008).

For a number of years now, the prudential supervision regulations on corporate governance (BIS, 1998 and 2006; Banca d'Italia, 1998 and 2008) have encouraged and promoted the formation of responsible, authoritative and independent boards, by the supervised entities, actively involved in the management of the banks and fully aware of the specific types of risks associated with the banks' decisions and operations; this condition, in fact, is now viewed as a prerequisite for the sound and prudent management of financial intermediaries (Carretta, Schwizer & Stefanelli, 2003). The importance of a responsible and participative board, in respect of the management of the banks, also emerges from the framework of the prudential supervision regulations (Basel 2, Pillar II), which qualifies the board as "the apex body of the internal governance system" (BIS, 2005; CEBS, 2006; Tarantola Ronchi, 2008); it ensures that the board may be given the task of supervising the all risks of banking business. Moreover, besides the governance aspects, bank board also has the role of Credit Risk Control Committees, with the task of expressing opinions on any significant credit risks in the bank portfolios.

The relationship between bank governance and risk taking has assumed a crucial importance, compared to the past, if we consider the recent trends in the behavior of operators and the current credit market environments.

With regard to the former, the evolution of the traditional model of credit intermediation towards an *originate to distribuite* rationale has driven managements to adopt a more 'free riding' attitude, at detriment of core business riskiness and, ultimately, of the stakeholders (Mayers & Majluf, 1984). The focus of management, in fact, might shift towards risk fragmentation techniques, above all, rather than on internal risk screening and loan monitoring processes, could underestimate the 'new risk creation' aspect, while focusing on the residual reported risk (Keys et al., 2009; Dell'Arriccia et al., 2008).

Regarding the latter, the worsening financial situation of households and enterprises – as a result of the ongoing economic crisis – is exposing financial intermediaries to the further continuous deterioration of the level of riskiness of their core business (Banca d'Italia, 2009; Abi Monthly Outlook, 2009), requiring a greater need of monitoring portfolio risk by the management. Several empirical analyses have confirmed how good governance can improve the performance of a company, especially in the face of a cyclical downswing of the markets (see for example, Colarossi & Giorgino, 2004).

Despite the importance of the topic, the empirical analyses examining how boards influence risk-taking in banks are really very few (Ahigbe & Martin 2008; Pathan, 2009; Cornett et al. 2009). In two cases, they compare the overall corporate risk measurements of the bank, as expressed by the market (total risk, idiosyncratic risk and systematic risk), with board independence (board size and proportion of independents on board, see Ahigbe & Martin 2008; Pathan, 2009) and some governance characteristics (the proportion of independents on the board and board committees, the proportion of the board with seats on other boards, the presence of an independent financial expert on the audit committee, see Ahigbe & Martin 2008); in another case, the risk is expressed through earnings management alone – as a qualitative measure of bank credit risk – and is compared only with board independence (board size and proportion of independents on board, Cornett et al. 2009).

This article will increase the existing literature, analyzing the relationship between board monitoring and the quality of the loan portfolios of listed Italian banks in the 2006-2008 period.

Compared with the existing literature, this article differs for several reasons, such as the nature of the relationship board monitoring-loan portfolio quality and the loan portfolio risk variables used for the econometric model.

The previous studies, in fact, express loan portfolio quality in terms of the ratio of Non Performing Loans to Total Loans (Cornett et al., 2009; Boudriga et al., 2009), or Non Performing Loans to Total Assets of the bank (Acharya, Hasan & Sauders, 2002). However, these are "aggregate" measurements representing the stock risk variables reported in the financial statements at the end of the year, and their limit is that they are not very clear. In particular, lower levels of Non Performing Loans cannot always be regarded as signs of the improvement of the loan portfolio quality and, therefore, of the bank's reduced exposure to risk; the outsourcing of debt recovery or securitization activities, the final writing off of bad loans and the transfer to other problem loan categories are several examples of situations that impair the full reliability of the analyses based on indicators calculated according to the bank's bad loans at the end of the year.

On the contrary, this study analyzes various different accounting proxies, with a view to understanding the quality of the bank's loan portfolio from different perspectives, such as risk creation in annual corporate management, migration, mitigation and the risk hedging decisions taken by the management in the year.

The focus of the article is important for the banking system in general, and especially in the case of the Italian situation due to the gradual deterioration of the domestic credit market, recently highlighted by the regulators and institutions, and by the significant role played by the forms of internal governance in countries like Italy, which are characterized by an *insider* type of industrial capitalism, with weak external governance mechanisms (Aganin & Volpin, 2003).

The remaining paper is organized as follows. Section 2 reviews the literature leading to the research hypothesis. Section 3 describes sample, variables and econometric model. Section 4 and Section 5 present, respectively, the regression results and the robustness check results. Finally, Section 6 concludes the paper.

LITERATURE REVIEW AND HYPOTHESIS

The older literature describes the board monitoring as the result of two specific characteristics of the board (Pincus et al. 1989; Collier, 1993; Peasnell et al., 2004; De Andres & Vallelado, 2008): the proportion of the independent directors and the presence of audit committee in board.

In the Italian case, the adoption of these governance mechanisms in the listed banks has been supported and promoted for a long time by the Consolidated Law on Finance, by the new rules on corporations, by the law of saving protection, by the Code on Corporate Governance (2006) and recently, by specific provisions on governance banking supervision.

The independence of directors in the boards is in fact a central theme in governance; within the banks, they take the role of counterbalance the executives and management, promote the proper functioning of the board and stimulate internal dialogue while reducing the areas of greater conflict of interest in the bank. Many empirical studies confirm that an independent board of directors has fewer conflicts of interest when monitoring managers. Klein (2002), Peasnell et al. (2004) support, in fact, that the presence of the independent directors in the board appears to be an effective corporate governance mechanism to reduce the agency problem and increase earnings quality. Some evidences indicate consistently that firms with more independent board members have higher quality earnings. Byrd et al. (2001) examine the effect of internal governance arrangements on the probability that a firm survives the economic crisis of the 1980s; they find that firms which survived the crisis had a greater proportion of independent directors in the board.

On the subject of the independents in the board, anyway, we underline a further strand of studies which shows that an excessive proportion of independent directors can limit the management advisory role of board (i.e., Yermack, 1996; Muth & Donaldson, 1998; Adams & Mehran, 2003; Fernandes, 2007). These studies typically refer to the fact that while independent directors increase the quality of monitoring, they may lack of sufficient knowledge on firm-specific information, leading to sub-optimal decisions. Adams and Ferreira (2007), Coles et al. (2008), Harris and Raviv (2008), indicate a trade-off between the advantages and disadvantages in the proportion of non-executive directors: inside directors add to the board information that outside directors would find difficult to gather; besides, executive directors facilitate the transfer of information between board directors and management.

In the same time, the existence of audit committee in board can have an important role in the monitoring action of the board. Supervision banking regulation and self-regulation promotes the adoption in the listed banks of such Committee with advisory and proposing functions on specific attributions of the board (i.e. supervision of adequacy of the bank's system of internal controls, audit of effectiveness of the process of accounting and financial reporting, preparation of accounting and corporate documents for the external auditors, Borsa Italiana, 2006; Banca d'Italia, 2008). Many studies focus on whether committee existence and independence are associated with enhanced board effectiveness. In general, Yermack (1996) confirms that the presence of the committees improves the action of management control and reduces the need to recognize economic incentives to management itself. Collier and Gregory (1999), Bronson et al. (2009) find greater audit committee independence to be associated with improved monitoring of the financial reporting process. On the contrary, only Anderson et al. (2003) find no evidences between audit committee independence and improved financial reporting.

There are no evidences in literature on the relation between board monitoring-loan portfolio quality in bank. Sumner and Webb (2005) examine the relationship between the structure of a bank's board (expressed by independents and also board size, board diversity, CEO duality) and the bank's loan portfolio choice on a sample of 300 bank holding companies in

1997; they find some consistence positive evidences. Cunat and Garicano (2009) study empirically how corporate governance of savings banks matters by studying the impact of the board composition and structure on loan losses, rating changes and the composition of the loan portfolio; their results confirm a clear impact of the human capital of the savings banks chairmen on the measures of loan book composition and performance. However, this study does not take in to account the traditional main risk of the banking business.

Other studies report the effects of corporate governance (i.e. strong board, board independence) on total bank risk, expressed by capital market ratio. Ahigbe and Martin (2008) identify links between capital market risk measures (total risk, idiosyncratic risk, systematic risk) and corporate disclosures and governance (this one expressed by the proportion of independents on the board and the board committees, the proportion of the board with seats on other boards, the presence of an independent financial expert on the audit committee in banks) on a sample of 768 financial services firms. They show that governance characteristics significantly explain the cross-sectional variation in the shorter-term and longer-term risk shifts. Pathan (2009) reports the positive effects of strong board (small board size, more independent directors, non restrictive shareholders rights) on bank risk-taking of a sample of 212 large US bank holding companies over the period 1997-2004; he uses only capital market ratio (total risk, idiosyncratic risk, systematic risk and asset return risk) to express the banking business risks of the sample. Cornett et al. (2009), instead, examine how corporate governance mechanisms – such as board size, board meeting, independents, board of director stock ownership, CEO duality - affect earnings management in US bank holding companies in the US; they find corporate governance plays at least some role in earnings and earnings management at large US banks, in particular, board independence constrains earnings management.

Considering the existent literature, our idea is that independent directors and the audit committee on board affect the effectiveness of board monitoring and, consequently, improve the loan portfolio quality in bank.

So, the following hypothesis is formulated:

(Hp1): The quality of the bank loans' portfolio is positively linked to the board monitoring (the existence of audit committee and the proportion of independent directors in board).

The analysis on the nature of the relation between the board monitoring and the loan portfolio quality in bank is however incomplete if we do not take into account the structure and internal functioning of the board. In fact, as other studies note, there are several bank governance characteristics that can affect how boards monitor and operate in firms. Particularly important points are board size, meeting activity, board diversity; evidences on the positive effects of these characteristics on board monitoring are however mixed in empirical studies (for a review see Carretta et al., 2007; Schwizer et al., 2009)[2].

Another important variable in the analysis is the assumption of duties by directors in other companies. The literature on this issue comes under the stream of studies on interlocking (intended as the connection between two or more companies through the share of one or more board directors, see Mizruchi, 1988), investigating the reasons for the existence of the phenomenon and its effects on the individual directors, the firm and the market/ area of reference in the different theoretical perspectives (resource-based theory, class based theory, bank hegemony theory).

With specific reference to the credit market, some studies confirm the benefits for banks in cases of natural ties (Ruigrok et al., 2003), resulting from the reduction of information asymmetries on the credit quality of the debtor (Pfeffer & Salancik, 1978) and from the ability to influence the company management and exercise stricter monitoring and control particularly in a period of declining performance (Mariolis, 1975; Richardson, 1987). In the same direction, Dooley (1969) shows how companies with poor credit have a greater chance of creating connections with the banks in an attempt to reduce uncertainties about the availability of financial resources. In the same direction, Mizruchi and Stearns (1988) show that firms with high leverage and increasing capital requirements create more connections at the board level with its own lenders. Further studies confirm the benefits of interlocking also on overall bank performance, tied to the position in the network of relationships and strategic/organization choice of the firm (Farina, 2007; Farina, 2009).

At the aggregate level, some studies emphasize how the existence of horizontal ties in the banking industry creates power relationships and facilitate collusion agreements between operators by imposing restrictions on competition in the credit market (AGCM, 2008). Regardless the type of interlocking (natural/horizontal), further studies confirm the benefits of individual directors of the bank, resulting from the position of over-boarded in terms of remuneration, maximizing of job opportunities, reputation, reputation and social prestige in the market (Zajac, 1988). In this light, Ahigbe and Martin (2008) report that other directorships held by directors may improve their credibility and so the monitoring role in board; they put in evidence that credibility may be greater for directors that hold seats on other boards, since these members clearly are sought after and have more extensive directly related experience.

On the other hand, theoretical considerations indicate that busy directors are bad for a firm: directors that sit on many boards have less time to monitor managers and thus to detect early symptoms of management self-dealing. In spite of this, corporate governance theory does not provide a clear insight on whether busy board members enhance firm performance, and previous empirical results are conflicting (Arranz-Aperte & Berglund, 2008).

Considering the existent literature, we also think that board size, board diversity, meeting activity and other directorships, as corporate governance characteristics of bank, can also affect monitoring board role and consequently influence the bank loan portfolio quality. So, the following hypothesis is formulated *(Hp2): The quality of the bank loan portfolio depends on* *bank governance characteristics (board size, board diversity, meeting activity, other directorships).*

SAMPLE, VARIABLES AND ECONOMETRIC MODEL

Sample and Data

The sample employed in the analysis comprises a totality of Italian-based banks, listed at Borsa Italiana SpA in 2006-2008; based on the amount of loans granted to customers by the banks[3], the measurement parameters of the sample amounts to 69.27% of the entire banking system in 2006, rising to 74.21% in 2007, and then dropping to 63.98% in 2008. It is an open sample, with regard to the delisting and M&As realized by the domestic banking system in the sample period.

The information about bank governance has been drawn from the Corporate Governance Reports and the public documents posted in the banks' websites; if the bank adopted the two-tier model, we have considered the only Supervisory Board because it expresses the monitoring function of the bank board[4]. While the loan portfolio data of the banks is drawn from ABI Banking Data. The database has no missing.

Measures of Loan Portfolio Quality in Bank

Compared with the existing literature, this article uses a number of accounting proxies to express the loan portfolio quality of a bank, which can be reconstructed based on an analysis of the Notes to the bank's financial statements (Table A.1.7, featuring the layout set forth in the Bank of Italy's Circular Letter No. 262/2005) and focus on different aspects of the portfolio, such as the creation of risk as a result of the year's management, migration, mitigation and the risk hedging decisions defined annually by the management, which all together define the quality of the portfolio, in terms of its riskiness according to a dynamic approach.

The adoption of accounting measures is preferred, in fact, to the capital market ratios used in previous analysis. The volatility of a security, in fact, incorporates the overall bank's business risk (credit risk, market risk, operational risk), while in the study we want to consider only the bank's credit risk exposure.

The ratios used are not just limited to the conventional quality indicator based on the Non Performing Loans contained in the portfolio. Figure 1, in fact, highlights how the Final Non Perfoming Loans are only the last component – preceded by loan write-offs, debt recovery, securitization and transfers to other loan categories – capable of impacting the riskiness of the loan portfolio, in the year, and, therefore, can hardly be representative of the overall dynamic quality of the portfolio. The same applies to the Final Problem Loans contained in the bank's portfolio.

Figure 1: Non Performing Loan Analysis per Year
Initial non-performing loans
+ New non-performing loans
- Write-off
- Recovery
- Sales/Securitized
- Transferred to performing loans
- Transferred to other problem loans
= Final non-performing loans
Source: authors' elaboration.

Based on these assumptions, the analysis has developed five variables capable of approximately explaining specific aspects of a loan portfolio quality of bank.

Dependent Variable 1 is the *Default Rate* (obtained as the *New Non Performing Loans*$_t$ / *Non Performing Loans*$_{t-1}$ ratio) and is a proxy of the new risk generated in the year by the bank's corporate management operations, since it is not affected by the downward variations resulting from the portfolio loan transfers to different categories, assignments, collections, write-offs.

As a rule, the bank's risk management efforts tend to privilege the fragmentation of risks, rather than risk screening and monitoring of the loan, especially in the case of "originate and distribute" credit intermediation models, which underestimate the creation of new risk and tend to focus their attention on the residual amount of risk reported in the financial statements. These considerations have been significantly confirmed by empirical studies, and by the recent market crisis, in Keys et al., (2009) and Dell'Arriccia et al., (2008), who confirm how asset securitization by banks has produced, over the years, less selecting loan screening processes, compared to the past. In these situations, active monitoring by the board can safeguard the stakeholders, driving towards the more efficient allocation of the financial resources, aimed at limiting the creation of new corporate risks and, consequently, preventing/opposing the appearance of new systemic crises.

Dependent Variable 2 is *Recovery Rate* (obtained as *Recovery of Non Performing Loans*$_t$/ *Non Performing Loans*$_{t-1}$ ratio) is a proxy of the bank's debt recovery capacity.

Monitoring by the board of the bank's debt recovery capacity can contribute to improving the loan portfolio recovery rate and minimize loan losses in the year. In particular, loan risk monitoring can be achieved – during the customer screening phase – also by selecting the most expedient hedging technique, based on the type of financial requirement expressed by each customer. With regard to this aspect, empirical assessments show how specific technical forms allow increased recovery rate control (De Laurentis & Riani, 2004); moreover, the subsequent monitoring of loan positions by the bank must necessarily be extended to the associated guarantees, in order to evaluate its congruence in time. Dependent Variable 2, therefore, outlines different aspects of the bank's monitoring activities, with respect to the congruence of the guarantees and the timeliness of the actions that can limit loan losses and prevent moral hazard problems. Unlike Dependent Variable 1, it outlines the bank's capability of minimizing the loan portfolio risk, however without hampering the positive income flow (interest/commissions) to the bank from the loan.

Dependent Variable 3 is called *Provisioning Rate* (obtained as *Loan Loss* $Provisioning_t$*/Customers* $Loans_t$ ratio), it expresses the amount of (specific and portfolio related) loan adjustments made by the bank in the year, net of any losses finally written off.

Loan adjustments are mandatory for banks as well (IAS 39, 2004) and constitute the main accounting instrument for hedging Expected Losses provided by the Basel Committee (BIS, 2004), and incorporated into the Italian banking regulations (Circular Letter No. 263 of 27 December 2006 by the Bank of Italy). The literature on the subject of loan loss provisioning takes into account, in the majority of cases, the earning smoothing hypothesis. The annual profit produced by the bank constitutes the parameter for assessing the effectiveness of the management's operations, therefore, disappointing results at the end of the year can justify the management's dismiss*al.* The volatility of corporate profits, moreover, is viewed as the principal source of risk by shareholders, which therefore requires congruent remuneration, thus inevitably increasing the cost of the bank's equity. The management, therefore, might be convinced to introduce earnings management policies aimed at stabilizing, in time, the profits reported in the financial statements (increasing allocations to provisions when profits are good and then "unfreezing" them when the profits shrink). Earnings management policies – which has always been opposed by the International Accounting Standard Board (IASB) – impair transparency in financial reporting, effectively preventing stakeholders from suitably assessing the bank's capability of producing income over the years[5].

Information asymmetries on the actual riskiness of the loan portfolio weighing on the stakeholders can further penalize them in the case of earnings management, facilitating an opportunistic behavior by the latter in respect of the hedging decisions related to any portfolio losses (Kanagaretnam, 2003). On the other hand, the incentive mechanisms introduced by enterprises are often linked to the profits produced by the bank, to the point of placing the management in a condition of conflict of interest. The analysis of this variable, therefore, aims at determining the benefits of board monitoring in contrasting similar harmful situations for the bank's stakeholders.

Table 1 provides an analytical description of the dependent variables adopted in the paper.

Table 1: Variables' Definition		
Dependent/Independent/Control Variables	Abrev.	Measures
Dependent Variables: Bank Portfolio Loans' Quality		
Default Rate	NNPLs	Ratio of New NPLs of the year to Gross Loans of previous year net of NPLs of previous year
Recovery Rate	RNPLs	Ratio of Recovery from NPLs to NPLs of previous year
Provisioning Rate	PR	Ratio of loan loss provisioning to customer loans
Independent Variables: Bank Board Monitoring		
Independents	IND	Percentage of independent directors in the boards per year
Audit Committee	AC	Constitution of the audit committee in board (dummy variable)
Independent Variables: Bank Governance Characteristics		
Board Size	BS	No. of executive and non-executive directors in the board
Meeting Activity	MA	No. of board meetings per year
Board Diversity	BD	No. of female directors in the board
Other Directorships	OD	Average of other directorships held by directors per year
Control Variables: Banking Business Structure		
Capital Ratio	CR	Ratio of equity to total assets
Loan Interest Rate	LIR	Ratio of customer interest rate to customer loans
Banking Business	BB	Ratio of customer loans to total assets
Δ Gross Loans	ΔGL	Rate of change of gross customer loans
Bank Size	BaS	Logarithm of annual total assets
Non Performing Loans/Customer Loans	NPLLs	Ratio of NPLs to customer loans
Doubtful loans	DLs	Ratio of Doubtful loans of previous year to Gross Loans of previous year
ROA Correct	ROAC	Ratio of Net Profit gross of loan loss provision to Total Assets
ROA	ROA	Ratio of Net Profit to Total Assets

Measures of bank board monitoring and governance characteristics

Based on the assumptions made and the existing literature, we have adopted the board monitoring, bank governance characteristics and banking business structure proxies. Board monitoring is defined by the percentage of independent directors serving on the board, and the

appointment of an audit committee in the years in question. Bank governance characteristics are defined by Board Size, Meeting Activity, Board Diversity and Others Directorships.
Table 1 provides an analytical description of the independent variables adopted and their measurement.

Control variables on banking business structure

Studies which identify the determinants of the loan portfolio quality in bank and the impact on company performance are investigating on specific dependency relationships with firm-specific and macro-economic variables linked to the frame of reference in which the bank operates. So our econometric analysis take into account some control variables, related to specific characteristics of banking business, that may affect the bank's portfolio quality.

Compared to the former, several studies confirm that the level of risk taking of the bank, that is to say the amount of Non Performing Loans (NPLs) that it generates, depends on its Capital Ratio[6].

By using the option-pricing model it is shown as a bank, in the absence of a capital requirement, tends to have excessive leverage and portfolio risk in order to maximize its shareholder value at the expense of the deposit insurance (Benston et al., 1986; Furlong & Keeley 1989). The bank risk-taking Capital Ratio relation should be reversed: a higher level of capitalization reduces the likelihood that the bank bears an opportunistic behavior in the choice of risk-taking and adopt robust and balanced risk management models to reconcile the expectations of profitability of the shareholders and the interests of depositors. The empirical results produced by Saurina and Salas (2002) on a sample of Spanish banks have shown, in fact, as with the increase of the capital ratio, the amount of outstanding Problem loans decrease[7]. The theoretical foundations for the appropriateness of imposing minimum capitalization constraints on banks meet to those conditions: higher capital implies higher losses for the banks' shareholders in case of default, and hence lower incentives for risk-taking (Repullo, 2002).

Nevertheless, some studies confirm results contrary to earlier and show that there is a direct relationship between capital ratio and risk taking. In particular, Kim and Santomero (1988), Rochet (1992) show that, against a particularly high cost of equity capital, to impose regulations to reduce the degree of leverage, leads to a decline in the bank's expected returns. The preferences of the bank's owners are located on the highest point of the efficient frontier of risk/return, pushing the bank to the recruitment of higher levels of risk. The importance of rules of risk-sensitive capital adequacy, therefore, is essential to avoid arbitrage on capital by banks (Jones, 2000).

A second variable which affects the loan portfolio quality of a bank is the performance, according to Boudriga et al. (2009), Godlewski (2004). Banks with high profitability are less pressured to revenue creation and thus less constrained to engage in risky credit offerings. Usually the measure of bank performance utilized in literature is Return of Assets (ROA), and some empirical studies find a negative relationship between performance and level of problem loans.

Another variable which affects the loan portfolio quality of a bank is the growth rate of the loan portfolio, according to Saurina and Salas (2002). The bank which implements aggressive expansion choices of its market share is exposed to dual nature phenomena that can worsen the quality of its portfolio: 1) less rigid criteria for lending to facilitate the entry of new customers with low creditworthiness, 2) adverse selection of customers as a result of the souring competitive tone on the credit market. The first phenomenon is easily understandable, while the latter deserves further investigation. An intermediary to capture new customers can enter new segments/markets by founding himself at a information disadvantage compared to banks already present; they do not obstruct the escape of the bad customers, while with a good chance they will reformulate the better pricing for the best customers without losing a considerable information asset and a long-term business relationship (Shaffer, 1998). This situation would allow the new entrant bank to capture the worst customers and expand its loan portfolio with the detriment of its quality. Even Keeton (1999) emphasizes the relationships of direct dependence between quality and growth of the loan portfolio: a rapid expansion of loans leads to a lower screening activity and a weaker monitoring activity which determines the riskiness of the loan portfolio.

An additional variable taken into account by literature regard the average rate of interest charged on loans. Using a sample of 2,470 U.S. commercial banks, Keeton and Morris (1988) confirm a positive relationship between the rate of interest charged by the bank on loans and the trend of Non-Performing Loans in the years 1979-1985. The application of a higher interest rate may be the direct consequence of the lending policies of intermediaries who intends to change their own level of risk; in this sense, the evolution of the average rate applicable to customers is a leading indicator of the level of risk taken and thus the possible deterioration of the overall quality of the portfolio. Similar results are proposed by Sikey and Greenwald (1991).

The bank size is considered by literature to be negatively linked to credit risk exposure. As noted by Hu et al. (2004), this could indicate that larger banks have more resources, and are more experimented to better deal with bad borrowers. Small banks, on the contrary, may be exposed to the adverse selection problem due to the lack of sufficient competencies and experience to effectively assess the credit quality of borrowers. Income creation pressure is also higher for small banks leading them to lend to ‘bad’ customers. Also Boudriga et al., (2009) and Salas and Saurina (2002) show an inverse relationship between problem loans and the bank size. However, should be considered as there are some contrary evidence on the relationship between bank size and NPLs (McNulty et al., 2001).

The final firm-specific variable considered in literature is the degree of specialization in the bank’s lending activity. The literature on this subject is very wide and spreads over comparable specific conditions, for example, the limits of the universal banking model, the choices of bank diversification by business, the bank income structure and the diversification of the portfolio. The choice of a competitive model specialized in banking business, allows the broker, from one side, an effective accumulation of economies of experience and, on the other side, losing economies of scope related to the appropriateness of implementing alternative strategies of related diversification (Johnson, 1996; Rajan, 1996; Santos, 1998; Schwizer, 1996). In terms of theory, diversification reduces the level of risk taking of the bank through a mechanism of compensation of gains/losses related to the overall product portfolio (Winton, 1999). An excessive competitive pressure towards the realization of profits, in fact, may lead the bank to take more risks and less accurate efficient selection of investment projects worth funding. Therefore, a bank who has a major share of non-interest revenues would be more selective and bring back to the budget a lesser amount of Non Performing Loans. The question, however is controversial, Hu et al., (2004), in fact, using a sample of 40 Taiwanese banks, it was showed that there was a direct correlation between revenue diversification and NPL during the 1996-1999 period. Micco et al., (2004), using a sample of banks in developing countries, noted a significant and positive relationship between the presence of Non-Operating Revenues and Problem Loans in the 1995-2002 period.

Among the macroeconomic variables, however, the one most used in literature is the economic growth rate (GDP) (Keeton & Morris, 1987; Sinkey & Greenwalt, 1991; Salas & Saurina, 2002) and the actual interest rate (Jimenez & Saurina, 2005). The relationship between the two variables and the riskiness of the loan portfolio is clearly a direct one. In many cases the econometric estimates were conducted by introducing lagged variables to consider the effect over time of the formation of the NPLs compared to the change of the economic cycle. For the purposes of this analysis, however, these variables are not considered as the three-year evaluation horizon makes them comparable to the constant, therefore, inadequate to explain the variability in the loan portfolio quality of the sample of banks.

Considering the existent literature, our idea is that Capital Ratio affect positively loan portfolio quality. While there is a inverse relationship between Loans Growth, Loan Interest Rate, Non Performing Loans and the loan portfolio quality of bank. Finally, there is no clear direction of the relationship between Banking Business and loan portfolio quality of the bank.
So we consider Capital Ratio, Loan Interest Rate, Credit Growth, Banking Business, Non performing Loans as control variables in our econometric model.

Econometric Model

We have used a Multivariate Regression Model (OLS) to test our assumptions, which expresses a loan portfolio quality of bank by means of the dependent variables identified in terms of generation of new risks, mitigation and risk hedging, and relates them to the independent variables linked to board monitoring, the bank governance structure and the business specificities of the bank as control variables. In particular, the adopted OLS model is as follows:

$Y_{ik} = \beta_0 + \beta_1 BS_i + \beta_2 AC_i + \beta_3 IND_i + \beta_4 MA_i + \beta_5 BD_i + \beta_6 OD_i + \beta_7 DLs_i + \beta_8 CR_i + \beta_9 ROA_i + \beta_{10} \Delta GL_i + \beta_{11} BB_i + \beta_{12} LIR_i + \beta_{13} BaS_i + \beta_{14} D07_i + \beta_{15} D08_i + \varepsilon_i$

where i identifies each bank in the sample ($i= 1, 2\ldots 76$); Y_{ik} is the portfolio quality of the i-nth bank expressed through the k-nth dependent variable $(k=1,2,3)$; β_1 , β_2 ,… β_{15} are the parameters that need to be estimated; $D07_i$ and $D08_i$ are the dummies relating to the year of observation for each variable relating to the i-nth bank, and are made equal to 1 in the case of either 2007 or 2008, while they are made equal to 0 in the case of 2006. The model also indicates the constant (β_0) and the error (ε_i). An analytical description of the single independent variables entered in the model is given in Table 1.

The econometric model in which the portfolio quality is expressed in terms of recovery rate (Dependent Variable 2), is as follows:

$Y_{ik} = \beta_0 + \beta_1 BS_i + \beta_2 AC_i + \beta_3 IND_i + \beta_4 MA_i + \beta_5 BD_i + \beta_6 OD_i + \beta_7 CR_i + \beta_8 \Delta GL_i + \beta_9 BB_i + \beta_{10} ROA_i + \beta_{11} BaS_i + \beta_{12} D07_i + \beta_{13} D08_i + \varepsilon_i$

We would like to specify that, in the econometric analysis in which the portfolio quality is expressed in terms of Provisioning Rate (Dependent Variable 3), the model further acquires the percentage amount of the Non Performing Loans (NPLLs), as another Independent Variable. Therefore, the econometric equation becomes the following:

$Y_{ik} = \beta_0 + \beta_1 BS_i + \beta_2 AC_i + \beta_3 IND_i + \beta_4 MA_i + \beta_5 BD_i + \beta_6 OD_i + \beta_7 CR_i + \beta_8 \Delta GL_i + \beta_9 BB_i + \beta_{10} LIR_i + \beta_{11} ROACorrect_i + \beta_{12} BaS_i + \beta_{13} D07_i + \beta_{14} D08_i + \beta_{15} NPLL_i + \varepsilon_i$

where $NPLL_i$ is the ratio between the non performing loans and the size of the customer loans in the i-nth bank's portfolio, in the year in question. We use in the last model a different version of ROA due to endogeneity problem. In this regression ROACorrect is a ratio on Net Profit gross of loan loss provisioning to total assets.

To avoid multicollinearity problems, the construction of the econometric models has followed a stepwise approach in accordance with the levels of correlation of the variables shown in Table 2.

RESULTS AND LIMITS

Main results

Table 3 illustrates the descriptive statistics of the sample; in particular, we consider 76 observations for the period 2006-2008. Table 2 shows the correlation between the variables. For brevity, the commentary on both tables is omitted. The assumptions made in Section 2 are tested empirically on a sample of Italian banks listed in the period 2006 to 2008. Tables 4, 5 and 6 show the results of the regressions carried out.

Table 2 - Correlation between some variables

	Variables	1	2	3	4	5	6	7	8	9	10	11
1	Board Size	1.000										
2	Board Meeting	0.191*	1.000									
		(0.099)										
3	Diversity (Gender)	0.011	0.130	1.000								
		(0.923)	(0.262)									
4	Other Directorships	0.082	0.018	0.197*	1.000							
		(0.480)	(0.874)	(0.087)								
5	Independents	0.347*	0.477*	-0.034	0.044	1.000						
		(0.002)	(0.000)	(0.774)	(0.709)							
6	Audit Committee	0.162	0.200*	0.004	0.122	0.189	1.000					
		(0.162)	(0.083)	(0.976)	(0.295)	(0.102)						
7	Capital Ratio	-0.083	-0.230*	-0.029	0.241*	-0.234*	0.130	1.000				
		(0.475)	(0.045)	(0.805)	(0.036)	(0.042)	(0.263)					
8	Loan Interest Rate	0.195*	0.030	0.139	-0.137	0.079	-0.085	0.044	1.000			
		(0.091)	(0.797)	(0.229)	(0.238)	(0.496)	(0.463)	(0.708)				
9	Doubful Loans	0.276*	0.281*	-0.154	0.013	0.175	0.025	-0.171	-0.008	1.000		
		(0.016)	(0.014)	(0.183)	(0.910)	(0.130)	(0.827)	(0.140)	(0.948)			
10	NPLs	0.122	0.320*	0.084	-0.098	0.043	0.182	-0.182	0.158	0.514*	1.000	
		(0.295)	(0.005)	(0.469)	(0.401)	(0.715)	(0.116)	(0.115)	(0.173)	(0.000)		
11	Bank Size	0.554*	0.113	0.103	-0.027	0.428*	-0.051	-0.388*	0.194*	0.126	0.031	1.000
		(0.000)	(0.332)	(0.374)	(0.818)	(0.000)	(0.663)	(0.001)	(0.094)	(0.276)	(0.789)	

*= The symbol represents the significance level at least at 10 percent

Table 3: Univariate Descriptive Statistics: Italian Listed Banks 2006 – 2008

Variables	N	Mean	SD	Median	Min	Max
Bank Portfolio Loans Quality						
Default Rate	76	0.01	0.01	0.01	0.00	0.04
Recovery Rate	76	0.24	0.19	0.20	0.00	0.66
Provisioning Rate	76	0.01	0.01	0.01	0.00	0.05
Board Monitoring						
Independents	76	0.49	0.28	0.44	0.00	1.00
Audit Committee	76	0.82	0.39	1.00	0.00	1.00
Bank Governance Characteristics						
Board Size	76	14.96	4.52	15.00	7.00	25.00
Meeting Activity	76	15.30	6.01	14.00	6.00	41.00
Board Diversity	76	0.03	0.04	0.05	0.00	0.12
Other Directorships	76	3.32	1.97	3.55	0.00	6.70

Table 3: Univariate Descriptive Statistics: Italian Listed Banks 2006 – 2008						
Variables	N	Mean	SD	Median	Min	Max
Banking Business Structure						
Capital Ratio	76	0.09	0.07	0.08	0.01	0.47
Loan Interest Rate	76	0.05	0.01	0.05	0.00	0.07
Banking Business	76	0.60	0.22	0.66	0.04	0.91
Loan Growth	76	0.16	0.16	0.13	-0.10	0.55
Bank Size	76	16.57	1.87	16.44	12.83	20.77
Non Performing Loans/Gross Loans	76	0.03	0.03	0.03	0.00	0.23
ROA	76	0.01	0.01	0.01	-0.02	0.02
ROA Correct	76	0.02	0.03	0.02	-0.01	0.11
Doubtful Loans	76	0.01	0.01	0.01	0.00	0.04

Table 4 reports the regression with Default Rates Dependent Variable 1. Adopting a stepwise approach, the three significant models are defined with an R-square between 54.8 and 58.8 percent.

Table 4: Regressions Results with Default Rate as dependent variable				
Variables	Pre sign	Model 1	Model 2	Model 3
Doubtful loans	+	0.348***	0.350***	0.378***
		(4.08)	(4.06)	(4.66)
ROA	-	-0.476***	-0.488***	-0.495***
		(-4.69)	(-4.69)	(-5.26)
Banking Business	+/-	-0.00141	-0.00132	-0.00226
		(-0.34)	(-0.31)	(-0.56)
Δ Gross Loans	+	0.0276***	0.0244***	0.0285***
		(4.71)	(4.13)	(4.96)
Loan Interest Rate	+	-0.0454	-0.0805	-0.0415
		(-0.62)	(-1.10)	(-0.59)
Capital Ratio	-	-0.0348***		-0.0324**
		(-2.76)		(-2.62)
Dummy 07		0.00274	0.00272	0.00210
		(1.38)	(1.34)	(1.07)
Dummy 08		0.00250	0.00265	0.00236
		(1.25)	(1.30)	(1.22)
Diversity (Gender)	+/-	0.0442*	0.0456*	0.0527**
		(1.87)	(1.89)	(2.36)
Other Directorships	+/-	0.000732	0.000439	0.000703
		(1.64)	(1.01)	(1.61)
Audit Committee	-	-0.000593	-0.000897	-0.000680
		(-0.27)	(-0.41)	(-0.33)
Board size	+/-	0.000142		
		(0.74)		

Table 4: Regressions Results with Default Rate as dependent variable				
Variables	Pre sign	Model 1	Model 2	Model 3
Board Meeting	+/-	0.000188	0.000251	
		(1.21)	(1.61)	
Bank Size	+/-		0.000984**	
			(2.11)	
Independents	-			0.00641**
				(2.08)
Intercept		0.00346	-0.0115	0.00522
		(0.70)	(-1.41)	(1.17)
N. Obs		76	76	76
adj. R^2		0.485	0.462	0.509
R.square		0.574	0.548	0.588
F-stat		6.429***	6.369***	7.478***
t statistics in parentheses, * p<.10, ** p<.05, *** p<.01 A weak collinearity between Doubtful loans, Banking Business and Δ Gross Loans is detected. The maximum level of VIF is equal 1.60, therefore it can be easily accepted as the typical critical value for multicollinearity is a VIF ≥ 10, (Fox, 1997).				

The results show an absence of full right relationship between board monitoring and the production of new risk by the bank in all the three models and refute the Hp1, if we take into account also the sign of the regressors. Only the independents, in fact, affect the dependent variable but with a sign contrary to our expectations. The result can be justified by a lack of interest or organizational shortcomings in the processes of governance and risk control. First of all, we refer to the logics originate and distribute at the base of the models as credit intermediaries of Italian banks (especially if listed), who neglect this aspect against almost deliberate of the overall delegated monitoring action on the entrusted. Then, the reference is to possible failures and deficiencies in reporting processes to the board (and to the independents) on exposure to the corporate credit risk in the processes of communication and information exchange among the independents, the audit committee and the internal control bodies[8], which could bring the independents, under conditions of greater information asymmetry in relation to the management against the executives, to make late decisions that could be of damage to the chances of credit recovery by the bank. We show how in this context time factor is crucial for an optimal management of credit recovery (Cornelli & Felli, 1994; Generale & Gobbi, 1996).

A further justification of the response may result from the absence of an adequate financial expertise and a "specialist" understanding the risk issues and management required by the independents and the audit committee, which prevent the correct use of information received from management in the taking of decisions within the board, especially in sectors such as banking characterized by high complexity of the business. The studies emphasize that with a greater emphasis on the role of monitoring of the board, the independents meet a lack of sufficient knowledge on firm-specific information, leading to sub-optimal decisions.

In this regard, recent studies on the boards of European banks emphasize that despite the growing pressure on board members to understand and monitor the risk management systems adopted by their companies, all executives directors stress that most non-executive directors needed to have a "clear overview" rather than a "detailed understanding" of these systems. Even New Basel Capital Accord requires bank board using more advanced capital measurement approached to possess a general understanding of their banks' risk system and detailed comprehension of associated management reports (Ladipo et al., 2008).

Even the characteristic structure of governance (Board Size, Other Directorships, Board Meeting) does not have any influence on the generation of new risk, confirming the above considerations at the level of full board; an exception is the Diversity of the board (positive sign), that contribute to improve the new risk generated during the year; this result confirm only partially Hp2.

Table 5 presents the regression on the Recovery Rate ad Dependent Variable 2. The three models have an R-squared running from 32.1 to 38.8 percent.

The Hp1 seems to have occurred in Model 1, 2 and 3; with reference to the Audit Committee, the sign of the coefficient is contrary to the expectations in all models.

About Independents, our hypothesis is only confirmed in Model 3 and the coefficient has the sign expected; just with reference to the recovery rate, the result seems not aligned to the studies supporting the disadvantages arising from the presence in large numbers of independents in the board (Dalton & Daily, 1998; Yermack, 1996; Bhagat & Black, 1998; Muth & Donaldson, 1998; Adams & Mehran, 2003; Fernandes, 2007).

The analysis confirms only partially the Hp2 in Model 3, demonstrating that Board Size, Board Meeting and Other Directorships and jointly contribute to improve the loan portfolio quality through an increased recovery rate; the signs are positive for both variables. About the first variable, this result confirms the works of Ruigrok et al. (2003) and Pfeffer and Salancik (1978); their analysis highlights the positive contribution of Board Size on the recovery rate and confirms the advantages of the larger boards in the advisoring activity of management of NPLs.

On the same aspect, other studies confirm that larger boards improve the human capital available to businesses and the well functioning and quality of decision-making of the board with the benefit of the overall company performance (Zahra & Pearce, 1989; Hill, 1982; Coles et al., 2008). The result agrees with De Andres and Vallelado (2008) who point out, ultimately, how the effects of board size on bank value express a trade-off between benefits (monitoring and advising) and disadvantages (coordination, control and decision-making problem) and a relationship between the two non-linear variables.

About the board meeting activity, results contrast with the thesis of Lorsch and MacIver (1989) and Mace (1986) that the board meeting does not improve the business performances if the decisions taken by the board are solving problems within business, in the specific case of recovery rate.

About Other Directorships, the result puts in evidence the benefits for banks in cases of ties and confirms previous studies (Pfeffer & Salancik, 1978; Mariolis, 1975; Richardson, 1987; Ruigrok et al. 2003).

Table 5: Regressions Results with Recovery Rate as dependent variable

Variables	Pre sign	Model 1	Model 2	Model 3
ROA	-	2.704	3.092	2.254
		(1.14)	(1.24)	(0.99)
Banking Business	+/-	0.201**	0.258***	0.223**
		(2.20)	(2.66)	(2.43)
Δ Gross Loans	-	0.118	0.0529	0.0984
		(0.91)	(0.40)	(0.75)
Capital Ratio	+	-0.525*		-0.502
		(-1.77)		(-1.66)
Dummy 07		0.0541	0.0456	0.0399
		(1.15)	(0.93)	(0.83)
Dummy 08		0.000984	-0.00126	0.000205
		(0.02)	(-0.03)	(0.00)
Diversity (Gender)	+/-	0.742	0.710	0.909*
		(1.35)	(1.24)	(1.68)
Other Directorships	+/-	0.0248**	0.0211**	0.0249**
		(2.39)	(2.02)	(2.37)
Audit Committee	+	-0.131**	-0.128**	-0.120**
		(-2.55)	(-2.44)	(-2.33)
Board size	+/-	0.00861*		
		(1.93)		
Board Meeting	+/-	0.00493	0.00687*	
		(1.35)	(1.83)	
Bank Size	+/-		0.00391	
			(0.35)	
Independents	+			0.142*
				(1.88)
Intercept		-0.0837	-0.109	0.0316
		(-0.83)	(-0.57)	(0.38)
N. Obs		76	76	76
adj. R^2		0.282	0.217	0.264
R.square		0.388	0.321	0.362
F-stat		3.682***	3.079***	3.693***

t statistics in parentheses, * p<.10, ** p<.05, *** p<.01
A weak collinearity between Doubtful loans, Banking Business and Δ Gross Loans is detected. The maximum level of VIF is equal 1.44, therefore it can be easily accepted as the typical critical value for multicollinearity is a VIF ≥ 10, (Fox, 1997).

Table 6 reports the regression with Provisioning Rate as Dependent Variable 3; the models proposed are of great strength that starts from 46.2 up to 50.4 percent.
The Hp1 is partially verified. How easy it was expected, the Audit Committee exerts a monitoring activity on the amount of provisions made by the management and is statistically significant in model 2 and 3. Instead, the Hp2 is not verified, except for the case of Board Meeting, that is statistical significant with a negative sign.

Control variables

About regression results with Default Rate as dependent variable (Table 4), in the three models Doubtful Loans, ROA and Total Assets are statistically significant. With regard to the Doubtful Loans, it shows like the sign obtained is consistent with expectations. A greater amount of Doubtful Loans in the previous year influences positively the default rate of the following year. ROA is also a variable statistically significant and the sign is consistent with previous studies (Boudriga et al., 2009; Godlewski, 2004). Finally, the bank size seems to positively influence the default rate. In this regard, the result obtained is in contrast with previous studies (Boudriga et al., 2009; Saurina & Salas, 2002).

Table 6: Regressions Results with Provisioning Rate as dependent variable

Variables	Pre sign	Model 1	Model 2	Model 3
NPLs	+	0.109***	0.112***	0.0939***
		(4.62)	(4.58)	(3.91)
ROACorrect	-	-0.196**	-0.198**	-0.148
		(-2.16)	(-2.08)	(-1.65)
Banking Business	+/-	-0.00230	-0.00169	-0.00299
		(-0.63)	(-0.44)	(-0.79)
Δ Gross Loans	+	-0.0123***	-0.0127***	-0.0129***
		(-3.07)	(-3.06)	(-3.10)
Loan Interest Rate	+	0.0698	0.0327	0.0523
		(1.03)	(0.48)	(0.75)
Capital Ratio	-	-0.0230**		-0.0207*
		(-2.05)		(-1.75)
Dummy 07		-0.000434	-0.000500	-0.000326
		(-0.24)	(-0.27)	(-0.17)
Dummy 08		0.00298	0.00305	0.00267
		(1.62)	(1.60)	(1.41)
Diversity (Gender)	+/-	0.00861	0.0138	0.000265
		(0.41)	(0.64)	(0.01)
Other Directorships	+/-	-0.000160	-0.000436	-0.000251
		(-0.40)	(-1.10)	(-0.61)
Audit Committee	+	0.00450**	0.00333	0.00391*
		(2.24)	(1.64)	(1.87)

Table 6: Regressions Results with Provisioning Rate as dependent variable				
Variables	Pre sign	Model 1	Model 2	Model 3
Board size	+/-	-0.000276		
		(-1.62)		
Board Meeting	+/-	-0.000304**	-0.000271*	
		(-2.17)	(-1.90)	
Bank Size	+/-		-0.000230	
			(-0.54)	
Independents	+			-0.00393
				(-1.34)
Intercept		0.0126***	0.0128*	0.00823*
		(2.79)	(1.70)	(1.88)
N. Obs		76	76	76
adj. R^2		0.409	0.362	0.359
R.square		0.504	0.464	0.462
F-stat		5.006***	4.550***	4.502***

t statistics in parentheses, * p<.10, ** p<.05, *** p<.01
A weak collinearity between Doubtful loans, Banking Business and Δ Gross Loans is detected. The maximum level of VIF is equal 1.49, therefore it can be easily accepted as the typical critical value for multicollinearity is a VIF $\geq$ 10 , (Fox, 1997).

Following the theories of the relationship lending, it argued that large banks have more difficulties to capture soft information. Therefore, this evidence is consistent with McNulty et al. (2001) and confirms that larger banks are less inclined to relationship lending (MacNulty, 2001; Bonaccorsi di Patti et al., 2005).

With reference to other control variables, in the three models Loans Growth and Capital Ratio are statistically significant. The sign of the coefficient coincides with the expected sign. Therefore, consistently with Furlong and Keeley (1989), Repulla (2002), Saurina and Salas (2002), the level of bank risk-taking is inversely related to the degree of capitalization. Furthermore, Loans Growth positively influences significantly the amount of NNPLs of the year. This result is consistent with Keeton (1999), Saurina and Salas (2002). Unlike other studies, however, it is underlined how Loan Interest Rate and Banking Business do not statistically influence significantly the default rate.

About regression results with Recovery Rate as dependent variable (Table 5), the effect of control variables are partially confirmed. It is shown how Banking Business is statistically significant in all three Models. Capital Ratio, however, is significant only in Model 1 and has opposite sign than expected. In particular, the assumption made in line with Salas and Saurina (2002) requires the existence of an inverse relationship between Capital Ratio and bank risk-taking, so the expected sign of the recovery rate is positive because a higher capital ratio improves the recovery rate of the bank, in conjunction with the assumption of less risky positions. In regression, however, the increases of the level of capitalization represents a decrease of recovery rate; this evidence agrees with some studies (Kim & Santomero, 1988; Rochet, 1992) and stresses as in the presence of a capital adequacy regulation with little risk sensitivity, the bank tends to focus on segments characterized by a higher risk/return profile. The sample analyzed seems to have taken a containment behavior of risk taking than the single probability of default, in the presence of high Capital Ratio. In contrast, in correspondence of a less risk-sensitive legislation, the recovery rate seems lower in banks that have a high Capital Ratio. It is noted, however, that the report in question is not stable and therefore these observations should be treated with caution[9]. The Banking Business variable improves the recovery rate and confirms the benefits of economies of specialization in the bank (Johnson, 1996; Rajan, 1996; Santos, 1998).

Finally, about the regression results with Provisioning Rate as dependent variable (Table 6), the effect of control variables has occurred in good part. NPLLs are significant and with positive sign, as expected: the amount of analytical adjustments depends positively on the NPLLs. Other variables are also significant, like Capital Ratio and Loan Growth. ROACorrect is only significant in two models. In the case of Loan Growth, the sign of the coefficient is in contrast with expectations. The expansion of the loan portfolio would increase the risk for the bank, then the level of adjustments on loans. In case of earning smoothing, the growth of the portfolio (and thus margins of profitability of the bank) should cause a rise of Loan Loss Provisioning. The analysis shows, however, the lack of earning smoothing and Loan Loss Provisioning focused only on certain loss, as proposed by IAS 39. Analyzing this result together with the evidence that emerged in the Dependent Variable 1, we confirm the tendency of the Italian banking market to the "originate and distribute" logic. The reduction in Provisioning Rate conducted in the presence of a growing loan portfolio may be justified by the intention of the management, to surrender to a third party claims arising from which derives the futility of corrections as a precaution[10].

After all, the banks that achieve higher ROACorrect are those that generally have a lower degree of risk taking and then make less provisioning. This result is also consistent with Hp1 and other studies (Boudriga et al. 2009; Godlewski, 2004).

Limits

Possible limitations in the analysis come from the failure to consider the professional skills in the board among the regressors which can affect the loan portfolio quality. Some studies show how the skills, experience, provenance and even popularity of the advisers could improve decision-making processes of the board and then business performance (Miller, 1981; Leontiades, 1982; Andrews, 1983; Huse & Rindova, 2001); others emphasize how the lack of skills in the board can generate more transaction costs as a result of a limited monitoring action on the management (Sapienza & Gupta, 1994). The consideration of this variable in the study excluded for too onerous data could confirm whether the weaknesses of the monitoring board also depend on the boards with deficient or inadequate skills and experience.

Further possible limitations of our results are related to the control variables used in the regressions. The first one is related to using a short-term horizon of the analysis (3 years), given the nature of the phenomenon under investigation, which has also led to the exclusion of lagged variables in the econometric model. Some studies adopt lagged variables to explain the formation of the NPLs in the bank. Boudriga et al. (2009) use lagged variables as the GDP_{t-1} and the amount of the Loan Loss $Provisioning_{t-1}$. The second variable results always statistically significant, while the delay of GDP is irrelevant in determining the amount of NPLs. In a more complex way, Salas and Saurina (2002) use larger time lags: the variable of Capital Ratio provides 2 and 3 years of delays, while the Loan Growth with a single lag time, with results contrary to the study of Boudriga et al. (2009). The present paper has chosen not to use lagged variables among the regressors because of a limited time horizon taken as a reference, which prevents substantially to express any possible volatility of the variables with the passing of time and then to grasp the effects on the dependent variables. In other works (Boudriga et al., 2009; Salas & Saurina, 2002) variables of bank's profitability (ROA, Net Interest Margin) were adopted, reaching often discordant and not significant results. Such limitations could be overcome in subsequent developments in the work.

ROBUSTNESS CHECK

In the paper we conducted several tests of robustness. In order to avoid multicollinearity problem we entered in regression the variables in respect of the correlations. The calculation of variance inflation factor (VIF) for the three models built indicates the absence of multicollinearity problems.

To control heteroskedasticity we conducted various tests. In particular, we performed Breusch-Pagan/Cook-Weisberg test for heteroskedasticity on dependent variable and all regressors. It was subsequently performed White general tests for heteroskedasticity (Table, 7, 8 and 9).

Table 7: Heteroskedasticity Test on Default Rate as dependent variable

Test	Model 1	Model 2	Model 3
Breusch-Pagan / Cook-Weisberg test chi2 (1)	4.94	6.49	7.58
Prob > chi2	0.0263	0.0109	0.0059
Breusch-Pagan / Cook-Weisberg test chi2 (13)	32.73	37.11	29.36
Prob > chi2	0.0019	0.0007	0.0020
White test chi2 (75) P-value	76 0.446	76 0.446	76 0.446

Table 8: Heteroskedasticity Test on Recovery Rate as dependent variable			
Test	Model 1	Model 2	Model 3
Breusch-Pagan / Cook-Weisberg test chi2 (1)	1.93	0.35	0.14
Prob > chi2	0.1647	0.5533	0.7100
Breusch-Pagan / Cook-Weisberg test chi2	7.68	12.25	5.32
Prob > chi2	0.7420	0.3454	0.8052
White test chi2 P-value	73.776 0. 4525	58.713 0. 5592	47.472 0. 5754

Table 9: Heteroskedasticity Test on Provisioning Rate as dependent variable			
Test	Model 1	Model 2	Model 3
Breusch-Pagan / Cook-Weisberg test chi2 (1)	22.19	21.98	44.18
Prob > chi2	0.0000	0.0000	0.0000
Breusch-Pagan / Cook-Weisberg test chi2	44.95	45.23	67.59
Prob > chi2	0.0000	0.0000	0.0000
White test chi2 P-value	76 0.446	76 0.446	76 0.446

The results of the tests are not unique. According to the test of Breusch-Pagan/Cook-Weisberg seems that the first model (new non-performing loans) and the third model (provisioning rate) have some problems of heteroskedasticity, while the second model (recovery rate) does not show any problem. As for the two models mentioned above was conducted a second regression with White's correction. The results, reported in Table 10 and 11, confirm the robustness of the regressions. About the results of the regressions, we substantially confirm previous considerations.

Table 10: Regressions Results with Default Rate as dependent variable, Robust estimation				
Variables	Pre Sign	Model 1	Model 2	Model 3
Doubtful loans	+	0.348***	0.350***	0.378***
		(4.44)	(4.51)	(4.88)
ROA	-	-0.476***	-0.488***	-0.495***
		(-3.64)	(-3.26)	(-3.75)
Banking Business	+/-	-0.00141	-0.00132	-0.00226
		(-0.32)	(-0.29)	(-0.54)
Δ Gross Loans	+	0.0276***	0.0244***	0.0285***
		(4.18)	(3.77)	(4.37)
Loan Interest Rate	+	-0.0454	-0.0805	-0.0415
		(-0.41)	(-0.68)	(-0.39)
Capital Ratio	-	-0.0348***		-0.0324***
		(-2.68)		(-2.68)

Table 10: Regressions Results with Default Rate as dependent variable, Robust estimation				
Variables	Pre Sign	Model 1	Model 2	Model 3
Dummy 07		0.00274	0.00272	0.00210
		(1.35)	(1.34)	(1.09)
Dummy 08		0.00250	0.00265	0.00236
		(1.24)	(1.23)	(1.28)
Diversity (Gender)	+/-	0.0442**	0.0456**	0.0527**
		(2.12)	(2.09)	(2.50)
Other Directorships	+/-	0.000732*	0.000439	0.000703
		(1.70)	(1.12)	(1.65)
Audit Committee	-	-0.000593	-0.000897	-0.000680
		(-0.28)	(-0.42)	(-0.32)
Board size	+/-	0.000142		
		(0.68)		
Board Meeting	+/-	0.000188	0.000251	
		(1.01)	(1.37)	
Bank Size	+/-		0.000984	
			(1.66)	
Independents	-			0.00641**
				(2.17)
Intercept		0.00346	-0.0115	0.00522
		(0.64)	(-0.99)	(1.08)
N. Obs		76	76	76
adj. R^2		0.485	0.462	0.509
R.square		0.574	0.548	0.588
F-stat		9.593***	12.00***	8.868***
t statistics in parentheses, * p<.10, ** p<.05, *** p<.01				

Table 11: Regression Results with Provisioning Rate as dependent variable, Robust estimation				
Variables	Pre Sign	Model 1	Model 2	Model 3
NPLs	+	0.109***	0.112***	0.0939**
		(4.62)	(3.04)	(2.16)
ROACorrect	-	-0.196**	-0.198	-0.148
		(-2.16)	(-1.30)	(-1.03)
Banking Business	+/-	-0.00230	-0.00169	-0.00299
		(-0.63)	(-0.34)	(-0.52)
Δ Gross Loans	+	-0.0123***	-0.0127**	-0.0129**
		(-3.07)	(-2.20)	(-2.11)
Loan Interest Rate	+	0.0698	0.0327	0.0523
		(1.03)	(0.47)	(0.80)
Capital Ratio	-	-0.0230**		-0.0207**
		(-2.05)		(-2.29)
Dummy 07		-0.000434	-0.000500	-0.000326
		(-0.24)	(-0.25)	(-0.16)

Table 11: Regression Results with Provisioning Rate as dependent variable, Robust estimation				
Variables	Pre Sign	Model 1	Model 2	Model 3
Dummy 08		0.00298	0.00305	0.00267
		(1.62)	(1.20)	(1.13)
Diversity (Gender)	+/-	0.00861	0.0138	0.000265
		(0.41)	(0.61)	(0.01)
Other Directorships	+/-	-0.000160	-0.000436	-0.000251
		(-0.40)	(-1.01)	(-0.57)
Audit Committee	+	0.00450**	0.00333*	0.00391*
		(2.24)	(1.72)	(1.93)
Board size	+/-	-0.000276		
		(-1.62)		
Board Meeting	+/-	-0.000304**	-0.000271	
		(-2.17)	(-1.25)	
Bank Size	+/-		-0.000230	
			(-0.71)	
Independents	+			-0.00393
				(-1.19)
Intercept		0.0126***	0.0128	0.00823
		(2.79)	(1.56)	(1.41)
N. Obs		76	76	76
adj. R^2		0.410	0.362	0.359
R.square		0.512	0.464	0.462
F-stat		5.006***	2.223**	4.095***
t statistics in parentheses, * p<.10, ** p<.05, *** p<.01				

CONCLUSIONS AND IMPLICATIONS

This paper investigates the relationship between the board monitoring and the loan portfolio quality in Italian banks listed in the 2006-2008 period.

The results of the analysis show an overall weakness of the board role in monitoring loan portfolio quality of the bank, with the subsequent damage of the interests of stakeholders. In limited cases of existence of a relationship between board monitoring and portfolio quality (recovery rate), a total contribution (Independents and Audit Committee) but negative for the bank is reported.

Possible explanations for these results can be identified at the system level, in the models of credit intermediation also popular among Italian banks that prefer the "originate and distribute" logic in the process of expectations, in which the business of origination seems to prevail at the expense of risk screening and monitoring of credit and the use of policy-loans oriented to fragmentation and subsequent allocation of risk in financial markets.

Further possible explanations for these results can be identified, for each bank, in the inefficiencies of the organizational and information processes underlying the system of internal governance of the bank. In this context, reference is made to possible delays or shortcomings in the contents of the report submitted to the board and audit committee by management or by the supervisory bodies of internal control (internal audit) which slow down or undermine the proper exercise of monitoring board damaging the interests of shareholders and stakeholders; a similar effect could be caused by deficiency of technical skills in risk management or of understanding of the logic underlying the management of risks in the bank, partly justified by an asymmetric information at the expense of independents against the executive directors.

The results are more encouraging when taking into account further structural features of bank governance. The attention to loan portfolio quality improves, in fact, if you look at the board at its structure level and overall organization (Board Size, Diversity, Board Meeting, Other Directorships) including the executives as well. The attention remains only on some measures of risk (recovery rate). In fact, the positive contribution to improve the quality of the portfolio (recovery rate), although partial, may result from the Board Size and Other Directorships, pushing to make some reflections on empirical studies and on the same supervisory framework that promotes the downsizing of the bank board but also helps to confirm the significance of both variables in supervisoring and advisoring of management. Finally, the Board Meeting has a positive effect on management of recovery rate and provisioning rate and it has no effects on default rate.

The analysis also shows the contribution to the loan portfolio quality by a greater Capital Ratio and a high Banking Business. The Loan Growth variable denotes particular problems: against its increase, banks experience increased non performing loans and take more risks not adequately countered by a rise in Loan Loss Provisioning. This result may confirm the gradual shift towards the originate and distribute model of Italian banks; an expansion of the portfolio in the absence of an adequate Loan Loss Provisioning can be read as the intention of management to originate loans that will soon be transferred to third parties and for which you do not retract the need to implement provisions.

These results reveal a worry lack of protection of the interests of the stakeholders especially in the context of banking crisis and gradual deterioration of the Italian credit market Among the possible resolutions at the system level, it is recommended a greater attention to the legislation in provisions to ensure adequate hedge limited not to certain losses only. A system of dynamic provisioning as the Spanish one could ensure adequate coverage for expected losses and reduced pro-cyclicality in the economy. A problem of transparency of bank balance sheets was also pointed out by regulators (Consob, 2008), therefore it is desirable that the standard setter define in a less ambiguous the criteria for derecognition of loans related to securitization, in order to enable all stakeholders in a position to appreciate the real situations of risk of intermediaries.

Considering the individual bank, an improvement in the action of board monitoring and overall governance on quality of the portfolio of the intermediary (and hence on the performance of the bank and the banking system) may result from the dissemination of the practices of boards induction and board member site visits already adopted by some European banks. These are solutions that, applied to the case of independents, can improve the knowledge of the banking business and related risks, stimulate and promote an active and conscious participation of the directors in management. For some European banks, the induction programs targeted to boards and visits at the banks' business divisions and functional units are the essential part of the process by which independents learn about risk and opportunities facing the business (Ladipo et al., 2008). However, these solutions must be accompanied by action and verification of adequacy of communication and reporting processes to the board currently implemented in the systems of internal governance, to ensure completeness, timeliness and accuracy of corporate information forwarded to top management. The rules of banking supervision and self-regulation on listed companies have shown considerable attention in promoting good governance in banks even through a greater accountability in the activities of the supervisory board of management and management of the bank. The regulators require individual members to be objective, capable and inquisitive, to learn about the activities of the bank and the risks it has assumed. An active and influential board is in fact one of the conditions to ensure a good and prudent management. To support the proper functioning of the board, discipline promotes, among other things, the adoption by intermediaries of efficient communication channels upwards and competent financial functions, legal and internal audit, and omits an explicit reference to promotion of measures for internal training and updating for the board, which may facilitate the understanding of dynamic and advance risk measures and enhance the contribution of governance in the presidium of a good and prudent business management to ensure the stakeholders and the banking system in the Country.

ENDNOTES

1 This paper is the result of a joint effort by the two authors. However, Valeria Stefanelli wrote the paragraph "Introduction", "Literature review and hypothesis", "Conclusions and implications" and sub-paragraph "Main results". Matteo Cotugno wrote the other paragraphs and sub-paragraphs of the paper.

2 On bank board size, supervision discipline argued and recommended the establishment of boards with non-plethoric sizes in order to facilitate the right internal functioning and organization of the board (Banca d'Italia, 2008).

3 In detail, the amount of loans granted to customers by Italian banks total € 2.054 billion in 2008, of which € 1.314 billion by stock exchange listed groups. The same variable features an increase, in 2007, of € 1.960 billion, of which € 1.454 billion by stock exchange listed banks. Lastly, the figure for 2006 totals € 1.890, of which € 1.309 by stock exchange listed banks; see Banca d'Italia (2006), pp. 210; Banca d'Italia (2007), pp. 247; Banca d'Italia (2008), pp. 214.

4 Assonime (2008) has considered the same criteria in its report on corporate governance.

5 It is for this reason, therefore, that the IASB has failed to support dynamic provisioning techniques based on the Expected Losses, imposing the implementation of provisions only with respect to the existing portfolio losses that have not yet been paid (Incurred Losses). This decision by the IASB has sparked a heated debate, given the existence of empirical assessments supporting the pro-cyclical nature of the

provisions based on Incurred Losses, for further information see: European Central Bank (2001), Cavallo and Majnoni (2002).

6 Under Circ. n.272 of 30th July 2008 the Bank of Italy, the NPLS are cash exposures and off Financial Statements in respect of a person subject to insolvency (including non-judicial determination) or basically similar situations, regardless of loss forecasts made by the bank. It is left out of consideration, therefore, the existence of any guarantees (real or personal) placed in defense of exposures.

7 The Problem Loans category includes, in addition to the NPLS, also the doubt Loans (DL) and Past Due Loans (PDL). Under Circ. n.272 of 30th July 2008 of the Bank of Italy, the DL are cash exposures and off-Financial Statements against persons in temporary situations of objective difficulties which may be expected to be removed in a reasonable period of time, while the PDL are exposures cash and off- Financial Statements other than those classified as bad, stranded or refurbished debts between exposures, which at the date of the alert, they are due for more than 90/180 days (with a continuing nature). In both evaluations (DL and PDL) it is left out of consideration the existence of any guarantees (personal or real) on the position.

8 A recent study confirms the boards of European banks as the "private session" between the audit committee and the head of internal audit, as recommended by the various Codes of Conduct, is a practice that still unstructured in 69% of the banks investigated are held when necessary and without a default frequency (Ladipo et al., 2008).

9 An alternative explanation may be proposed with reference to the theories of relationship banking (Petersen & Rajan, 1994; Cole, 1998; Berger, Rosen, Udell, 2001). The analysis showed a statistically significant inverse relationship between capital ratio and size of the bank. Smaller banks are better capitalized and often, according to the theory, more oriented to relationship lending (Scott, 2004; Berger et al., 2005; Udell, 2008). They therefore may be more inclined to make loans with a lower level of guarantees, given the presence of soft information.

10 It is emphasized that in the presence of continuing involvement (IAS 39) the bank, even if transferred to a special purpose vehicle, is required to enroll loans in the budget. So, a contraction in the size of the loan portfolio does not necessarily correspond to an assignment of credits.

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THE FEDERAL OPEN MARKET COMMITTEE AND THE FEDERAL FUNDS RATE: A TEST OF MARKET EFFICIENCY

Michael Young, Longwood University
Frank Bacon, Longwood University

ABSTRACT

Using standard event study methodology from the finance literature, this study tested the semi-strong form efficient market hypothesis by analyzing the effects of the Federal Open Market Committee (FOMC) January 22, 2008 announcement of a 75 basis point cut in the Federal Reserve (Fed) rate on the risk adjusted rate of return on a sample of 50 bank stocks. Specifically, is it possible to earn an above normal return on a publicly traded stock when the FOMC announces a FED funds rate cut? According to the semi-strong form efficient market hypothesis, it is not possible to consistently outperform the market — appropriately adjusted for risk — by using public information such as FED fund rate cut announcements. This type of information should impound stock price sufficiently fast to disallow any investor to earn an above normal risk adjusted return. Using standard risk adjusted event study methodology with the market model, the study analyzed 10,761 observations for the event period from the 50 publicly traded banking firms comprising the majority of the total US bank market capitalization and the S&P 500 Index to examine the impact of the FED funds rate cut on stock price. Evidence here supports the bank sample's swift and positive risk adjusted rate of return reaction to the FED fund rate cut announcement. However, the study results fail to support the semi-strong form efficient market hypothesis in the strictest format since investors are able to earn an above normal return during the 10 day window following the announcement. Likewise, results suggest the possibility of trading on this information up to 8 days prior to the announcement.

INTRODUCTION

How fast does the stock market react to new publicly announced information? According to Fama (1970), market efficiency can take on three forms: weak form efficiency, semi-strong form efficiency, and strong form efficiency. In a market that is weak form efficient, stock prices should react so quickly to all past information that investors are unable to earn an above normal return based on their knowledge of this information. Semi-strong form efficiency hypothesizes that stock price is a reflection of all publicly available information. Stock price should react efficiently enough to all public information that investors are unable to earn abnormal returns. Strong form efficiency hypothesizes that stock price is based upon both private and public information. In this case, the market reacts to an event based on information that is held within the confines of the firm prior to its public announcement, suggesting that investors were able to act on inside information illegally.

The Federal Reserve System (FED) plays a substantial role in the fluctuations of both the economy and the financial markets. The FED controls monetary policy in the United States. One monetary policy gauge of the Federal Reserve System is the Federal funds rate, or the FED funds rate, which is considered one of the "primary indicators of the stance of monetary policy" (Mishkin 393). The FED funds rate is the interest rate at which overnight loans of reserves are made from one bank to another. The FED funds rate is set as a target rate by the Federal Open Market Committee (FOMC) and has a direct impact on interest rates throughout the economy. Increases or decreases in the FED funds rate are immediately reflected in the stock market as the market often reacts quickly to changes in the Federal Reserve's policy due to its significant impact on the money supply and the economy. According to Bacon and Weinstein (2008), trading on FED funds rate change announcements can produce above normal stock market returns in the short run.

Similar to the Bacon and Weinstein study (2008) this study focuses on the information efficiency surrounding the announcement of a FED funds rate cut. The FOMC has 8 regularly scheduled meetings during each calendar year. The FOMC, made up of the Chairman of the Federal Reserve, the President of the New York Fed and the other Federal Reserve presidents sets the federal funds rate. The FED funds rate is the rate that banks charge each other when they are lending to other institutions. These loans are usually very short term, most being overnight. The FED funds rate has always been closely monitored by investors because it is the only rate that the Federal Reserve actually controls.

Starting in the summer of 2007 the economic outlook worsened. From 2004-2006 the FED funds rate increased by 25 basis points at almost every meeting that the FOMC held. In late 2007 the rate started to fall and in January of 2008 the FOMC held an unscheduled meeting and cut the rate 75 basis points. Even though the FOMC historically holds eight scheduled meetings per year, if immediate action is necessary, an unscheduled meeting is called. To provide a more pure test of market efficiency, this study selected this "unscheduled called" meeting to mitigate potential "expectation" bias associated with regular meetings. This drop of 75 points was one of the largest in the previous 5 years. Lowering the FED funds rate is usually an effort to expand the economy by encouraging increased borrowing and spending. Therefore, the rate is usually very low during economic recession and higher during economic peaks.

According to the efficient market hypothesis, the stock market should immediately respond to public announcements of FED funds rate changes making it impossible for an investor to "beat the market" or to make an above normal return on their investment by acting on such information. This study investigates whether an investor can in fact achieve an above normal return by capitalizing on public announcements of changes in the FED funds rate target.

The study tests the efficient market hypothesis by assessing the investor's ability to earn an above normal return in the short run by acting on FED funds rate change announcements.

The purpose of this event study is to determine the impact of a FED funds rate cut announcement on the risk adjusted rate of return on a sample of 50 bank stocks. Specifically, how fast does the market price of the firms' stock react to the FED funds rate cut announcement? This research tests whether the announcement directly incorporates the strong form, semi-strong form, or weak form of the efficient market hypothesis based on the timing of the announcements and the modifications in stock price that occur.

LITERATURE REVIEW

Fama (1970, 1976) defined market efficiency in three forms: weak-form, semi-strong-form and strong-form. Weak-form efficiency deals with the notion that no investor can earn an above normal economic return by developing trading rules based on past price or return information. Numerous studies (Fama, 1965; Alexander, 1961; Fama and Blume, 1966; Granger and Morgenstern, 1970) support the random walk theory in support of weak form efficiency.
If the market is weak form efficient, then stock price reacts so fast to all past information that no investor can earn an above normal return (higher than the market or the return on the S&P 500 index) by acting on this type of information. Annual accounting reports are an example. These documents summarize the "past operations" of the firm and when mailed out are past information. If an investor receives the report and buys the firm's stock after discovering the firm had high earnings for the period and then stock price does not rise, the market is said to be efficient with respect to past information and is weak form efficient.

Semi strong-form market efficiency states that no investor can earn an above economic return based on any publicly available information. Tests of semistrong form efficiency (Fama, Fisher, Jensen, and Roll, 1969; Ball and Brown, 1968; Aharony and Swary, 1980, 1981; Joy, Litzenberger, and McEnally, 1977; Watts, 1978; Patell and Wolfson 1984; Scholes, 1972; Kraus and Stoll, 1972; Mikkelson and Partch, 1985; Dann, Mayers, and Raab, 1977) document the claim that no investor can earn an above normal return on publicly available information such as accounting statements, stock splits, dividend announcements, sale of stock announcements, repurchase of stock announcements, block trades, and earnings announcements.

If the market is semi-strong form efficient, then stock price reacts so fast to all public information that no investor can earn an above normal return (higher than the market or the return on the S&P 500 index) by acting on this type of information. Public announcements of stock splits, repurchases, dividend increases are an example of public information. If one buys the stock on the announcement and still does not make an above normal return, the market is semi-strong form efficient.

Strong-form efficiency theory suggests that no investor can earn an above economic return from using any information, public or private. Studies on the validity of strong form efficiency offer mixed results (Jaffe, 1974; Finnerty, 1976; Givoly and Palmon, 1985; Friend, Blume, and Crockett, 1970; Jensen, 1968). A large body of literature cites numerous anomalies that question market efficiency theory.

If the market is strong form efficient, then stock price reacts so fast to all information (public and private) that no investor can earn an above normal return (higher than the market or the return on the S&P 500 index) by acting on this type of information. In this case, the market reacts to an event within the confines of the firm (or secret information) when it occurs even before it is publicly announced. For this to occur, investors must act on inside information, which is illegal. If one buys the stock on the event and still does not make an above normal return, the market is strong form efficient.

"Because information is reflected in prices immediately, investors should only expect to obtain a normal rate of return" (Ross 342). However, does market efficiency hold for public announcements of FED funds rate changes? Weak form efficiency states that a company's stock price is based on past prices and information, while strong form efficiency argues that the price is a reflection of all information, public and private. While both of these theories have merit, this study asserts that FED funds rate changes are reflected in the price of a company's stock according to the semi-strong form of efficiency, indicating that all public information available determines the price of the stock.

According to Bacon and Weinstein (2008), trading on FED funds rate change announcements can produce above normal stock market returns in the short run. Goukasian and Whitney (2008) find the market's reaction to announcements by the FOMC is positive and above normal when compared to broad market indexes. These positive movements do not come on the event date but rather surface on the day following the event date. This suggests that it takes some time for the market to digest the decision before a reaction.

METHODOLOGY

This study sample consists of 50 large banks that consist of the majority of total US bank market capitalization and are all traded on the NYSE as shown in Table 1 below. Historical stock prices and the corresponding S&P 500 Index were found on Yahoo Finance and the January 21, 2008 meeting date was found on the Federal Reserve website.

Table 1. Study Sample

Bank of America	Citi Bank	Wells Fargo	Royal Bank of Canada	Bank of Montreal
Sun Trust	Capital One	JP Morgan	Barclays	Deutsche Bank
Canadian Imperial Bank of Commerce	American Express Company	State Street Corporation	Northern Trust Corporation	M&T Bank
NY Mellon	Lloyds Banking Group	Banco Santander	PNC Financial Services	Fifth Third Bancorp
1st Source Corporation	U.S. Bancorp	Zions Bancorp	West Coast Bancorp	HSBC Holdings
Bancorp South	Regions Financial	Trustmark Corporation	KeyCorp	BB&T
Mizuho Financial Group	Bank of Nova Scotia	First Citizens Bank	ING Group	Morgan Stanley
Comerica Inc.	Toronto Dominion Bank	TCF Financial Corp.	Hudson City Bank	Raymond James Financial
Bank of Hawaii	BOK Financial Corp.	Washington Trust Bancorp	City National Corp.	Valley National Bancorp
Bancorp South	Webster Financial Corp.	Credit Suisse Group	UBS	Bryn Mawr Bank Corp.

To test semi-strong market efficiency with respect to public announcement of the FED funds rate cut and to examine the effect of the announcement on stock return around the announcement date, this study proposes the following null and alternate hypotheses:

$H1_0$: *The risk adjusted return of the stock prices of the sample of bank firms is not significantly affected by the FOMC press release information on the announcement date.*

$H1_1$: *The risk adjusted return of the stock prices of the sample of bank firms is significantly positively affected by the FOMC press release information on the announcement date.*

$H2_0$: *The risk adjusted return of the stock prices of the sample of bank firms is not significantly affected by the FOMC press release information around the announcement date, as defined by the event period.*

$H2_1$: *The risk adjusted return of the stock prices of the sample of bank firms is significantly positively affected by the FOMC press release information around the announcement date, as defined by the event period.*

This study uses the standard risk adjusted event study methodology from the finance literature. The FOMC FED funds rate cut announcement date (day 0) was obtained from federalreserve.org. The required historical financial data, i.e. the stock price and S&P500 index during the event study period was obtained from the internet website http://finance.yahoo.com/.

T he historical stock prices of the sample companies, and S&P 500 index, for the event study duration of -180 to +30 days (with day –30 to day +30 defined as the event period and day 0 the announcement date) were obtained.

Then, holding period returns of the companies (R) and the corresponding S&P 500 index (R_m) for each day in this study period were calculated using the following formula:

$$\text{Current daily return} = \frac{\text{(current day close price – previous day close price)}}{\text{previous day close price}}$$

A regression analysis was performed using the actual daily return of each company (dependent variable) and the corresponding S&P 500 daily return (independent variable) over the pre-event period (day –180 to –31 or period prior to the event period of day –30 to day +30) to obtain the intercept alpha and the standardized coefficient beta.

For this study, in order to get the normal expected returns, the risk-adjusted method (market model) was used. The expected return for each stock, for each day of the event period from day -30 to day +30, was calculated as:

$$E(R) = \text{alpha} + \text{Beta}\ (R_m),$$

where R_m is the return on the market i.e. the S&P 500 index.

Then, the Excess return (ER) was calculated as:

ER = the Actual Return (R) – Expected Return E(R)

Average Excess Returns (AER) were calculated (for each day from -30 to +30) by averaging the excess returns for all the firms for given day.

AER = Sum of Excess Return for given day / n,

where n = number of firms is sample i.e. 50 in this case

Also, Cumulative AER (CAER) was calculated by adding the AERs for each day from -30 to +30.

Graphs of AER and Cumulative AER were plotted for the event period i.e. day -30 to day +30. Chart 1 below depicts Average Excess Return (AER) plotted against time. Chart 2 below depicts Cumulative Average Excess Return (CAER) plotted against time.

QUANTITATIVE TESTS AND RESULTS

Did the market react to the announcement of the FED funds rate cut? Was the information surrounding the event significant? A'priori, one would expect there to be a significant difference in the Actual Average Daily Returns (Day -30 to Day +30) and the Expected Average Daily Returns (Day -30 to Day +30) if the information surrounding the event impounds new, significant information on the market price of the firms' stock (see AER graph in Chart 1 below). If a significant risk adjusted difference is observed, then we support our hypothesis that this type of information did in fact significantly either increase or decrease stock price. To statistically test for a difference in the Actual Daily Average Returns (for the firms over the time periods day -30 to day +30) and the Expected Daily Average Returns (for the firms over the time periods day -30 to day +30), we conducted a paired sample t-test and found a significant difference at the 5% level between actual average daily returns and the risk adjusted expected average daily returns. Results here support the alternate hypothesis $H2_1$: The risk adjusted return of the stock price of the sample of firms is significantly positively affected around the announcement date as defined by the event period. This finding supports the significance of the information around the event since the market's reaction was observed.

Is it possible to isolate and observe the sample's daily response to the announcement of the FED funds rate cut from day -30 to day +30? If so, at what level of efficiency (weak, semi-strong, strong form according to efficient market theory) did the market respond to the information and what are the implications for market efficiency?

Another purpose of this analysis was to test the efficiency of the market in reacting to the FED funds rate cut announcement. Specifically, do we observe weak, semi-strong, or strong form market efficiency as defined by Fama, 1970, in the efficient market hypothesis? The key in the analysis or tests is to determine if the AER (Average Excess Return) and CAER (Cumulative Average Excess Return) are significantly different from zero or that there is a visible graphical or statistical relationship between time and either AER or CAER. See AER and CAER graphs in Charts 1 and 2 below. T-tests of AER and CAER both tested different from zero at the 5% level of significance. Likewise, observation of Chart 2 (graph of CAER from day –30 to day +30) confirms the significant positive reaction of the risk adjusted returns of the sample of firms tested, up to 8 days prior to the FOMC FED funds rate cut announcement.

The graph in Chart 2 demonstrates that the FOMC FED funds rate cut announcement had a significant positive impact on the firm's share price up to 8 days prior to announcement day 0 and swift and immediate increase on day 0. In fact, the sharpest increase in stock price and the corresponding risk adjusted rate of return occurred between days -1 and +1 leaving a narrow window of opportunity for an investor to earn a large above normal return by acting the rate cut news. Therefore, the evidence tilts more toward support the alternate hypothesis $H1_1$: The risk adjusted return of the stock prices of the sample of bank firms is significantly positively affected by the FOMC press release information on the announcement date. For the sample of firms analyzed, an investor is able to earn an above normal risk adjusted return by acting on the public announcement of the FED funds rate cut. As of the announcement date, the firms' stock prices had not completely adjusted to the new information embedded in the rate cut news. In fact, after the announcement, stock price rose significantly up to day +10 in an apparent overreaction and then steadily drifted downward to day +30 to pre event period levels. This is not entirely consistent with the semi-strong form market efficiency hypothesis which states that the stock price reflects all publicly available information. Interestingly, the results for this sample suggest significant insider trading activity up to 8 days prior to the announcement.

Figure 1. AER vs. Time

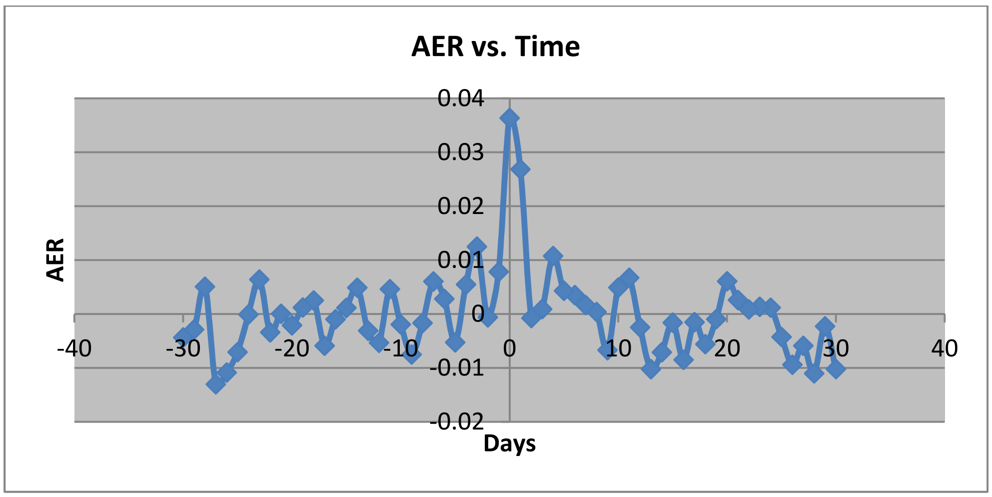
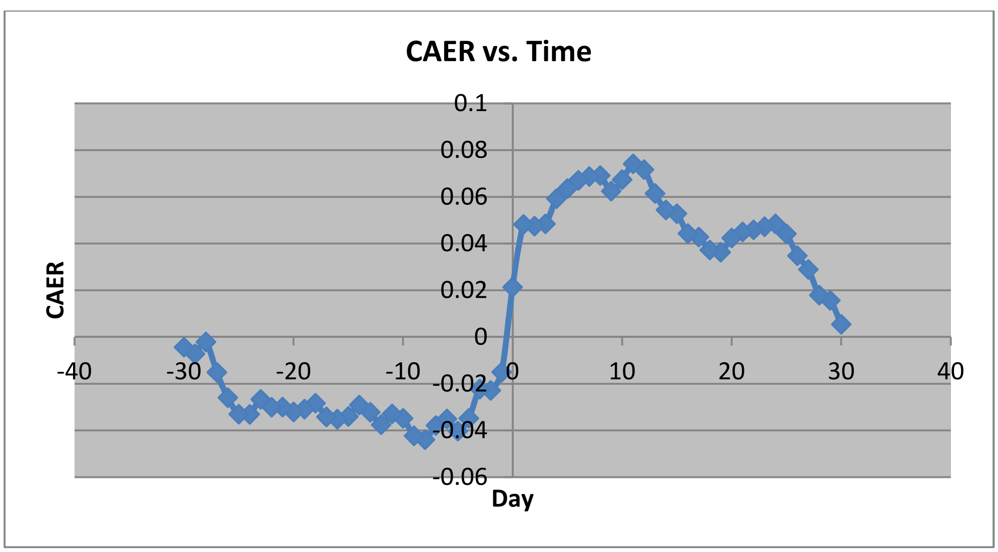


Figure 2. CAER vs. Time



CONCLUSION

This study tested the effect of the unscheduled FOMC January 22, 2008 announcement of a 75 basis point cut in the FED funds rate on the stock price's risk adjusted rate of return for a selected sample of 50 banking firms traded on the NYSE. Using standard risk adjusted event study methodology with the market model, the study analyzed 10,761 recent observations on the fifty publicly traded firms and the S&P 500 market index. Appropriate statistical tests for significance were conducted. Results show a significant positive market reaction prior to the rate cut announcement and around the event or announcement day. Findings fail to completely support efficient market theory at the semi-strong form level as documented by Fama (1970). Similar to Bacon and Weinstein (2008), this study suggests that investors can earn above normal returns around FED funds rate cut announcements in the short run. Also, like many other event study findings in the finance literature (stock options, repurchase, dividend announcements etc.), apparently trading activity on the basis of this information surfaced prior to it being made public.

Specifically, for this study the FED funds rate cut announcement is viewed as a positive signal by bank stock investors who believe lower interest rates will initiate the desired expansionary economic activity. Investors appear to receive the expansionary monetary action as a signal from the FED that the future growth of the economy and the banking system in particular will increase. Goukasian and Whitney show that there are abnormal returns on broad market indexes, such as the S&P 500, after FOMC announcements. If the S&P 500 is experiencing abnormal returns and the selected bank stocks are outperforming the S&P, then holders of bank stock should be optimistic about returns after FOMC meetings that cut rates.

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CLEARINGHOUSE LOAN CERTIFICATES DURING THE PANIC OF 1893

Christopher Hoag, Coe College

ABSTRACT

Do riskier banks borrow more from a lender of last resort? If liquidity provision by a lender of last resort suffers from a moral hazard problem, then banks that assumed additional risk before a panic borrow more from a lender of last resort when a panic actually strikes. This paper considers clearinghouse loan certificates held by New York Clearing House member banks during the panic of 1893 as an example of a lender of last resort. The paper attempts to link loan certificate borrowing to pre-panic risk factors. Participation in asset markets and exposure to seasonal currency withdrawals do not explain loan certificate borrowing for national banks. Individual bank level data show that loan certificate borrowing did not suffer from a moral hazard problem during this panic.

INTRODUCTION

Are riskier banks more likely to borrow from a lender of last resort? Lender of last resort facilities subject participating banks to moral hazard (Bernanke, 2008). If banks know that emergency liquidity will be readily and cheaply available during a panic, then banks may take additional risk before the panic strikes. During the panic, risky banks fund their liquidity needs by excessive borrowing from the lender of last resort. Those banks that took on extra risk will need to borrow more from a lender of last resort.

Unfortunately for modern researchers, it is difficult to obtain information on borrowing from a lender of last resort. Central banks prefer to hoard information about borrowing from lender of last resort facilities. (Officials at the Federal Reserve recently released information about borrowing from the Fed during the most recent crisis 2007-2010 only after this paper was written.) If investors learn that a particular bank borrowed, they may infer that the borrowing bank could be insolvent. Instead, we consider the historical example of clearinghouse loan certificates. Before the establishment of the Federal Reserve, the New York Clearing House (NYCH) orchestrated the defense against numerous financial crises that occurred during the second half of the nineteenth century. The NYCH was a voluntary association of New York banks designed to clear the balance of payments among members. Moen and Tallman (2000) show that clearinghouse membership in New York and Chicago permitted state banks to suffer fewer deposit withdrawals when compared to nonmembers during the panic of 1907. An important component of the defensive architecture was a lender of last resort provision called clearinghouse loan certificates that provided secret interbank loans to needy banks. In the case of clearinghouse loan certificates, conservative banks would lend money to riskier banks in need of liquidity. But the moral hazard problem provides a disincentive for conservative banks to subsidize risk-taking banks.

Sprague (1910) and Wicker (2000) highlight the collective action problem for NYCH member banks. If conservative NYCH member banks perceived that risky banks were free riding on the liquidity provision of clearinghouse loan certificates, then understandably the conservative banks would be less willing to contribute to a defense against the panics. Linking bank risk and loan certificate use would suggest that the NYCH could not undertake stronger defenses (such as pooling bank reserves) because conservative lending banks would be subsidizing risky borrowing banks. If a collective action problem had not prevented the NYCH from expanding its capability as a lender of last resort, then perhaps founding the Federal Reserve would have been unnecessary.

To determine if ex ante risk led to panic borrowing, this paper tests if the volume of loan certificates borrowed is sensitive to proxies for risk characteristics during the panic of 1893. Several economic historians propose various factors that contribute to bank risk. Specifically, we correlate loan certificate issues to individual NYCH member banks with proxies for asset market participation and exposure to agricultural seasonal withdrawal. We also include risk factors drawn from predictors of bank failure.

The 1893 data indicate that neither asset market participation nor exposure to withdrawals from the interior can substantially explain loan certificate borrowing for national banks. When risk is measured according to traditional historical metrics, member banks did not plan to use loan certificate borrowing to fund additional risk. That is, loan certificates did not suffer from a moral hazard problem during this panic. Hence, the lender of last resort provision of the clearinghouse loan certificates did not contribute to a collective action problem for NYCH defense against the panics.

HISTORY

The history and operation of NYCH loan certificates have received treatment elsewhere (Cannon, 1908; Timberlake, 1984; Gorton, 1985). In summary, loan certificates were invented by the New York Clearing House in the nineteenth century to provide interbank loans to members during recurrent periods of financial stringency. Loan certificates were available only to clearinghouse member banks during financial crises and operated through the clearing mechanism. Each business day, clearinghouse members met to settle net check payments. The net clearing system created a group of debtor banks and a group of creditor banks. The loan certificates allowed a bank with a favorable balance at the NYCH to loan money to debtor banks with an unfavorable balance.

The NYCH operated its loan certificate program as follows. If a bank had an unfavorable balance at the clearinghouse during a financial crisis, the debtor bank could submit securities (stocks, bonds, or commercial paper) to a committee of clearinghouse officers. The debtor bank received a loan certificate in exchange for the collateral securities, which were valued at a discount and backed by a joint redemption pledge of the member banks. The debtor bank could then tender the loan certificate to the creditor bank as a substitute for payment. The loan certificate temporarily discharged the debtor bank of its liability to the other member banks in the daily clearing. A creditor bank in possession of the loan certificate of the debtor bank could likewise use the loan certificate in future clearings as a substitute for payment. Alternatively, the creditor bank could hold the certificate and earned interest on the security (usually 6% or 7% per year, approximately the maximum legal rate) paid by the debtor bank. Debtor banks would pay off their loan certificates as the financial crises eased by calling in and redeeming the loan certificates. At the height of a crisis, nearly all balances were settled using loan certificates and not using reserves such as coin or currency.

Clearinghouse loan certificates served as an early lender of last resort program. Banks that were in need of liquidity could borrow loan certificates. Banks would submit the loan certificate in place of reserves in the daily check clearing. Thus, the bank borrowing loan certificates temporarily substituted the loan certificate for a payment of reserves to another member bank. In this way, clearinghouse loan certificates effectively allowed secret interbank loans among member banks. However, the loan certificates are not equivalent to reserves because they did not represent reserves in the vault and they were not paid out to depositors. Unlike smaller clearinghouses in later years, the loan certificates of the NYCH never circulated as money outside the associated banks in 1893 (Cannon, 1908) or even in later panics (Andrew, 1908). Instead, loan certificates helped to expand individual bank loans during financial crises. If a bank made a loan to a customer, some of the proceeds of the loan could eventually be deposited in other banks and would result in an unfavorable balance at the Clearing House for the loaning bank. With the use of the loan certificates, a bank could expand its loans without incurring a loss of reserves. To the extent of my knowledge, no bank was ever refused borrowing loan certificates after presenting collateral of adequate quality. In general, borrowing loan certificates did not subject the borrowing bank to additional monitoring. Banks loaned money for various purposes during crises. For example, Moen and Tallman (2010) argue that banks borrowed the loan certificates to import gold during the crisis of 1907.

This paper focuses on net loan certificate borrowing rather than actual borrowing. Banks that withdrew loan certificates could also hold the certificates of other banks. In fact, several banks held more certificates than they had borrowed. Banks might hold offsetting credits to borrowing for several reasons. For example, borrowing banks could receive loan certificates through the clearing mechanism on days when they were a net creditor, hence their net borrowings would decrease. Further, some banks approached the loan committee to take out loan certificates but then did not use them in the clearing mechanism. That is, although the loan committee would record a withdrawal of loan certificates, the bank would not actually have borrowed any money from another bank, and in this case the bank effectively loans money to itself. A bank might take out loan certificates and then not use them to ensure that the bank had access to enough loan certificates in case of later need. The associated banks limited aggregate issues, although ceilings on loan certificate issue were increased when necessary and were never binding upon the banks.

DESIGN

Scholars of banking policy express concern that a lender of last resort could contribute to a moral hazard problem (Moore, 1999). According to Freixas, Giannini, Hoggarth, and Soussa (2002), lenders of last resort can offer liquidity to illiquid banks or provide capital to insolvent banks. Anticipated assistance from a lender of last resort could affect the behavior of banks in two ways. First, liquidity provision by the lender of last resort reduces incentives for a bank to maintain its own reserves. A bank would desire to hold fewer easily marketable assets if inexpensive access to liquidity were available during panics. In addition, if the lender of last resort's intervention increases the probability that risky assets pay off due to the facility's mitigation or prevention of panics, then the banks could decide to take greater amounts of risk before the panic strikes. Second, more direct involvement by the lender of last resort, such as the rehabilitation of insolvent banks, could provide additional encouragement for banks to hold riskier assets. Recently, some authors have come to doubt the prevalence of moral hazard (Goodhart, 1999).

Contrary to the assumption of moral hazard, theoretical work suggests that the presence of a lender of last resort need not cause banks to take additional risk. Martin (2006) and Repullo (2005) derive models that allow banks to choose the probability that their risky assets will have a positive payout, where a lower probability of success leads to a higher payout. Both authors show that banks choose the same probability of a high payoff for their risky assets regardless of the presence or the absence of a lender of last resort. As for bank liquidity, Repullo (2005) finds that banks will decrease their reserves in response to the presence of a lender of last resort, meaning the bank will hold a larger proportion of risky assets in its portfolio. But in these models the lender of last resort cannot directly affect the probability of high payoffs of risky assets through its maintenance of an orderly market, removing one motive for acquiring additional risk. Though they do not model a lender of last resort specifically, Brusco and Castiglionesi (2007) show that interbank deposits and high enough levels of capital and interbank deposits can prevent banks from investing in a risky asset.

Imagine that moral hazard encourages banks to subsidize risk with borrowing from a lender of last resort. In our case, banks that were members of the clearinghouse had the opportunity to take more risk and could then fund this risk during panics through the vehicle of loan certificates. But our case involves a number of banks, each of which may take different levels of risk. Thus, a moral hazard story requires at least two features of the data: 1) banks eligible to borrow from a lender of last resort exhibit elevated risk compared to banks without the ability to borrow and 2) in large samples agents that take more risk should actually borrow more loan certificates from the lender of last resort. We do not test the first proposition of moral hazard, whereby banks increase risk under insurance. For example, we could compare whether clearinghouse members took more risk than nonmembers. But no one argues that access to clearinghouse membership increased bank risk. In fact, the literature pursues the opposite argument: clearinghouses monitored and limited the risk-taking of member banks (Gorton & Mullineaux, 1987). This paper focuses on the second characteristic of moral hazard: were loan certificates used by banks with greater *ex ante* risk characteristics? If banks suffered from a moral hazard problem, then bank risk should relate to panic borrowing. If risky banks did not borrow, as we find in the data, then moral hazard did not play a role in the use of loan certificates. We use variation in risk within the clearinghouse membership to determine if risk correlates with loan certificate use among clearinghouse members. While under moral hazard all members of the clearinghouse would have an incentive to take additional risk relative to banks outside the clearinghouse, the data show that only some of the member banks carried high levels of risk. Perhaps bank officers had different preferences over risk.

The purpose of the paper is to explain individual net clearinghouse loan certificate use in terms of *ex ante* risk assumed by the individual bank. Previous historical and empirical work suggests a list of risk factors that may influence the need for aid from a lender of last resort. We draw risk factors of loan certificate borrowing from historical analysis and from predictors of bank failure.

A first factor is due to risk on the liability side of the balance sheet. In the nineteenth-century United States, banks in the interior often deposited funds with money center banks in New York in order to obtain interest. Periodic agricultural activity, such as planting and harvesting, create a seasonal transactions demand for money. At harvest time, banks on the agricultural interior of the country would withdraw cash from money centers such as New York. Kemmerer (1910) observes that financial crises in the U.S. often coincided with seasonal fluctuations of the money supply. Both Myers (1931) and Sprague (1910) discuss the effect of seasonal interior deposits on the New York banks.

Sprague and Myers measure the exposure of New York national banks to withdrawals from the interior. Bank balance sheets distinguish between deposits owed to other banks and deposits owed to ordinary depositors. Deposits owed to banks are more likely to originate from interior banks. Hence, we can describe banks vulnerable to a seasonal withdrawal by deposits owed to other banks as a fraction of total deposits, or BANKBAL. Several large New York national banks, known as "interest-paying" banks, based their business on these bankers' balances (Hoag, 2005). These large national banks owed a high fraction of their deposits to other banks (presumably located in the interior) rather than to ordinary individual depositors.

Both historians and contemporary bankers expressed concern that deposits from the interior represented withdrawal risk. Sprague (1910) and Wicker (2000) believe that bankers' balances decreased the willingness of banks to cooperate during panics. A prominent banker of the period, George S. Coe, declared in an important 1884 address to NYCH members that banks holding large fractions of interior deposits were "almost alone in being compelled to seek protection from the loan committee, by a pledge of their securities" (Sprague, 1910, p. 377). Further, Wicker (2000) argues that the panic of 1893 originated in the interior and propagated to money markets. Subsequent empirical literature confirms that bank suspensions on the interior relate to real activity. Carlson (2005) demonstrates that states with greater commercial failures experienced greater bank suspension rates. Weak agricultural performance influenced local banking markets. Dupont (2009) shows that states with larger decreases in crop yields suffered a higher fraction of bank suspensions. Thus, we might expect city banks that hold interior balances to be more likely to suffer withdrawals, and hence more likely to require loan certificates. For example, Calomiris and Mason (2003) find that bankers' balances are negatively related to bank survival probability during banking crises of the Great Depression, though perhaps there is not a strong relationship for city banks.

According to one authority, bankers' balances were also related to asset market participation. Myers links bankers' balances to placing loans with brokers on the call loan market. Myers describes how a handful of national banks held the bulk of the deposits due from banks and used them to finance call loans to the stock exchange (Myers, 1931, p. 270-1). Myers notes that nearly one-half of all loans of New York national banks were demand loans during the period 1879-1904. Myers describes how the volume of call loans closely tracks aggregate banker's balances of New York national banks in the years before 1904. Presumably, state bank investment strategies for bankers' balances mirrored national bank allocation decisions. Thus, we also would like to control for investment in financial assets.

A second factor is due to risk on the asset side of the balance sheet. Several theoretical models motivate bank runs by asset risk. If asset prices fall, then depositors may liquidate deposits in anticipation of bank insolvency. In the context of banking panics, the asset usually consists of corporate debt or equity. Calomiris and Gorton (1991) present empirical evidence suggesting that bank panics followed substantial stock market devaluations.

The proportion of financial assets held by the bank relative to total loans proxies asset market participation. Congress did not grant national banks the privilege of holding stocks or corporate bonds directly, interpreted to mean that they were forbidden (Robertson, 1968, p. 65-6). Instead, banks loaned money to brokers through demandable call loans. A precondition for a call loan was stock collateral, and one mechanism of obtaining collateral was through the vehicle of certified checks. According to Knox (1908), certified checks were originally a verification by the bank that the check's author had adequate funds in his account to cover the check. Eventually, the banks "over-certified" checks, or certified them without the check's author having deposited funds. As Knox (1908) states (p. 185):

> Thus, a stock broker would buy a line of stocks with a check certified by his bank, and on sale of his stocks make his account good with the proceeds, or if a sale was not immediately made, make his account good with a loan upon the stocks as collateral. The banks doing this business were necessarily very often at the complete mercy of their dealers, and losses were frequently made when the brokers failed in their speculations.

Banks used over-certification of checks as an off-balance sheet bridge loan to finance stock trading and eventually trade in produce (Myers, 1931, p. 282-5). Initiating a call loan required stock collateral. Obtaining stock collateral necessitated a payment to the seller. To avoid this paradox, banks made a one-day loan to brokers in the form of certified checks. We proxy the exposure of the bank to asset markets by certified checks over deposits, or CERCHK.

A second proxy for participation in asset markets might be ownership of stocks or corporate bonds. Even though national banks did not possess the privilege of holding non-government securities, these items do appear on national bank balance sheets. Perhaps national banks could acquire these items as a result of bankruptcy or foreclosure. Alternatively, banks could have been ignoring the provision of the law or documenting the assets of subsidiary holding companies. We measure asset holdings relative to total loans, or STOCK/LOAN.

While historical work cited deposit withdrawals from interior banks and stock market risk as the two most important measures of risk, we consider additional risk metrics. We borrow empirical predictors of bank failure from White (1984) and Wheelock (1992). If bank depositors thought bank failure was more likely, they would be more likely to withdraw their deposits, and hence the bank would be more likely to require and infusion of liquidity from a lender of last resort. White and Wheelock use several additional proxies to explain failure rates in the 1920s and 1930s. First, we measure capital adequacy using the ratio of bank (book) capital to total assets, CAP/ASSET. White argues that capitalization is related to the risk of bank failure. Bank equity provides a cushion for depositors in case of bank failure. A second proxy for bank weakness is net undivided profits (surplus) to total loans, PROFIT/LOAN. Banks with poorly performing assets will be in a weaker condition before the panic and could be more likely to require external aid. A third risk factor is the size of the bank. Larger banks may have access to more diversified holdings, and therefore be less likely to need emergency lending. Following Wheelock (1992), we capture the size of the bank by the natural logarithm of its total assets, LNTOTAL.

Two final risk factors are the reserve ratio and the type of bank charter held. If banks held a higher proportion of reserves to deposits, then all else equal they should be better prepared to withstand substantial withdrawals. We measure the reserve ratio, RESRAT, as the sum of gold reserves plus currency reserves divided by deposits. In practice, national banks may have netted out deposits due from other banks, but the regression coefficients remain similar regardless of which measure of the reserve ratio used. Also, STATE is an indicator variable taking the value one if and only if the bank holds a state charter. Some authors consider state banks to be more risky than national banks because they were less heavily regulated. Some of these factors help to predict bank illiquidity: see the May, 2005 version of working paper for more discussion.

DATA

The data consist of call report balance sheets submitted to regulators by the banks of New York City in 1892-3. The dual banking system required state banks and national banks to submit reports at different times. The dataset uses balance sheet data from both state (September 19) and national (October 3) banks on two different call report dates. Since the dates of these two balance sheets are only two weeks apart, we treat this data as though it were from one date. We use two balance sheets from December 1892 (December 9 for the national banks and December 15 for the state banks) to represent the pre-panic balance sheet. Again, we treat these two balance sheets as occurring on the same date. Since there is some question about exactly when the panic actually begins, we choose the December balance sheet that is before the earliest stage of the panic.

Some of the call report dates happened to fall during the panic of 1893. Sprague (1910) and Wicker (2000) describe the historical evolution of the panic. According to Sprague's chronology, the panic of 1893 proceeded in three phases. The first stage of the crisis occurred in February 1893, when a prominent railroad failed and banks curtailed their loans to brokers. The second stage concerned the collapse of stock prices in May due to bank failures in the West and South. The third stage began in "the third week of July" when "a second wave of distrust of the banks spread over the West and South" (Sprague, 1910, p. 175). Some of the banks at least partially suspended payments for the month of August. Loan certificates were first issued on June 21, 1893, and all were redeemed by early November.

Table 1: Variable Definitions and Summary Statistics of the Data
(64 NYCH member banks)

Variable	Description	Mean	Min.	Max.
NETLC/DEP	Net loan certificates borrowed to deposits in Sept / Oct	-0.004	-0.304	0.212
BANKBAL	Bankers' balances to deposits	0.241	0	0.750
CERCHK	Certified checks to deposits	0.094	0	1.209
STOCK/LOAN	Other stocks and bonds to total loans	0.089	0	0.551
CAP/ASSET	Capital to asset ratio	0.106	0.009	0.278
PROFIT/LOAN	Net profits (surplus) to total loans	0.143	0.023	0.324
LNTOTAL	Logarithm of total assets	15.774	14.17	17.413
RESRAT	Reserve ratio	0.231	0.168	0.323
STATE	1 for a state bank, zero otherwise	0.281	0	1

Source: Bank balance sheet data on New York Clearing House member banks

Table 1 summarizes the data. The data include net loan certificate borrowing by 64 national and state New York Clearing House member banks in September/October 1893. The dependent variable, NETLC/DEP, is the ratio of net clearinghouse loan certificates to pre-panic deposits. Naturally, we expect larger banks to require larger amounts of clearinghouse certificates in case of an emergency, so we weight loan certificate issues by the size of the deposit portfolio of the bank. The December 1892 balance sheets provide the rest of the variables which determine the risk status of the bank before the panic. We will use the December balance sheets to predict loan certificate borrowing during the panic.

TEST

This section describes the test of the relationship between net loan certificate borrowing and exposure to risk characteristics. The empirical strategy is to correlate risk factors taken from the December 1892 bank balance sheets two months before the panic began with net borrowing of loan certificates during the panic using the September/October balance sheet for state and national banks. The assertion is that banks more heavily exposed to risk should be more likely to suffer deposit withdrawals and therefore should be more interested in obtaining assistance from a lender of last resort.

Instead of a structural model, we employ a reduced form approach including only those variables that are predetermined at the time of the panic. The reduced form approach shows the effect of ex ante risk on loan certificate borrowing. In a structural model, we could predict panic outcomes for the bank, such as withdrawals by depositors (whether by individuals or by other banks) on the basis of our risk factors. Then we could predict borrowing by loan certificates as a function of the percentage change in deposits for the bank. But the bank’s risk could still influence borrowing during the panic, since banks that know they are risky may decide to borrow more in anticipation of further withdrawals. Hence the coefficients in the structural model are not the coefficients of interest. Since we are interested in the effect of ex ante risk on borrowing, we use the reduced form. To test the hypothesis of moral hazard, we employ a simple linear cross-sectional regression of net loan certificate borrowing on the risk characteristics of the bank, the independent variables BANKBAL, CERCHK, STOCK/LOAN, CAP/ASSET, PROFIT/LOAN, LNTOTAL, RESRAT, and STATE.

RESULTS

Model 1.1 of Table 2 presents initial OLS estimates. Using a Wald F test, the data reject the hypothesis that the coefficients are jointly zero ($p = 0.028$), so the risk factors have some explanatory power. Model 1.2 presents a final model, where the omitted variables (BANKBAL, STOCK/LOAN, CAP/ASSET, PROFIT/LOAN, LNTOTAL) are statistically insignificant (Wald test, $p = 0.56$). A White test for heteroskedasticity was only marginally statistically significant (p

= 0.078), and the results remain similar with a heteroskedasticity correction, so we present ordinary OLS results. We now consider tests of hypotheses.

Table 2: Regression Results: Predictors of Net Loan Certificate Borrowing		
Variable Name	Model 1.1	Model 1.2
BANKBAL	0.059	
	(0.75)	
CERCHK	-0.116	-0.147**
	(-1.57)	(-2.45)
STOCK/LOAN	0.032	
	(0.29)	
CAP/ASSET	-0.169	
	(-0.70)	
PROFIT/LOAN	-0.255	
	(-1.20)	
LNTOTAL	-0.011	
	(-0.47)	
RESRAT	-0.496	-0.648*
	(-1.35)	(-1.94)
STATE	-0.045	-0.058**
	(-1.32)	(-2.25)
CONSTANT	0.344	0.176**
	(0.91)	(2.18)
R-squared	0.26	0.20
Number of Observations	64	64
Notes: Dependent variable: NETLC/DEP, or net clearinghouse loan certificates to deposits (t-scores in parentheses) * = significant at the 10% level, two-tailed test ** = significant at the 5% level, two-tailed test		
Source: Bank balance sheet data on New York Clearing House member banks		

The data suggest that holding bankers' balances does not lead to borrowing loan certificates. In Model 1.1, the coefficient on bankers' deposits is positive but small and statistically insignificant (p = 0.46). Holding bankers' balances does not appear to be an important explanation for loan certificate withdrawal by New York banks. Although banks with connections to the interior did suffer greater deposit drains, the risk did not cause a greater use of loan certificates. The conclusion that national correspondent banks were not more likely to take out loan certificates is unexpected given Wicker's characterization of the panic of 1893 as a withdrawal by country banks.

Asset market participation does not lead to positive net borrowing of loan certificates. Surprisingly, the variable CERCHK was small but negative and statistically significant at the 5% level in Model 1.2 ($p = 0.028$). Further, the variable STOCK/LOAN was small and statistically insignificant in Model 1.1 ($p = 0.77$) and does not survive elimination of insignificant variables. The result suggests that banks that invested more heavily in asset markets were not more likely to require loan certificates.

Increased liquidity does lead to less borrowing from a lender of last resort for national banks. As expected, the coefficient on the reserve ratio (RESRAT) was negative and the marginal effect was large and marginally statistically significant ($p = 0.057$). Holding greater reserves reduces the need to borrow liquidity from a lender of last resort. Other variables tend to have their expected sign, although some are statistically insignificant. Banks did not borrow more based upon lower book capital or size.

This paper has not considered the panic from the perspective of a foreign currency crisis. Miller (1996) and Friedman and Schwartz (1963) emphasize the international factors leading to a currency crisis. Sprague (1910, p. 191-2) describes how some banks used loan certificates to finance gold imports, but apparently not in substantial quantities until the end of July. Additional holdings of gold as reserves (rather than legal tender notes) do predict lower use of loan certificates in October, but the variable is not statistically significant (not reported).

In summary, neither participation in asset markets nor holding bankers' balances predicts greater borrowing by loan certificate for national banks. Moral hazard does not seem to be a substantial concern for loan certificate borrowing. Loan certificates apparently did provide liquidity to illiquid banks. National banks that held a larger fraction of reserves did have greater liquidity and therefore borrowed less.

CONCLUSION

We do not observe riskier banks borrowing more from a lender of last resort during the crisis of 1893. Empirical risk factors were not consistent predictors of net loan certificate borrowing by NYCH member banks during the panic of 1893. Since risky banks did not borrow more loan certificates, we do not observe the operation of moral hazard behavior in this sample. Banks exposed to seasonal withdrawals or banks participating in asset markets did not resort to greater borrowing of NYCH loan certificates. The loan certificate data do not support the assertion that the NYCH defense against the panics suffered from a collective action problem.

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DETERMINANTS OF PRICE DISCOUNTS IN BANKING ASP SYSTEMS

William Richmond, Western Carolina University
Paul Nelson, University of Rochester

ABSTRACT

This research examined data associated with 260 contracts between an ASP and its client banks to assess the factors affecting the price discount given to the banks. Incumbency, bank size, contract length, pricing structure, sales person, and bank efficiency are examined and their relative importance estimated. Incumbency, bank size, pricing structure, sales person, and bank efficiency all affect price. Pricing structure (fixed-fee versus variable, per unit pricing) has a significantly larger impact than does incumbency, sales person or bank efficiency.

INTRODUCTION

In September, 2011, there were 7,436 financial institutions insured by the FDIC. Of these 7,436 institution, 6769 (90%) were small with assets less than $1 billion (FDIC, 2011). These small banks and savings institutions are critical components of their local economy, but to survive and succeed, they have to be competitive with the large financial institutions. Critical to competing is both the ability to deliver the set of services expected by their customers and to manage their costs effectively. In both delivering their services and in managing costs, banks rely on their information systems.

Like many other organizations, some small banks outsource their IT. IT outsourcing is a $163 billion industry (McCue, 2004), and almost every aspect of IT has been outsourced. Banks take different approaches to outsourcing including using an Application Service Provider (ASP). An ASP provides its banks with access to a set of applications ranging from core banking systems to e-banking systems. The ASP vendor tracks usage and may charge based on that usage, based on the number of users, or it can charge a single, monthly fixed fee. The fee structure and prices charged are negotiated between the ASP and the bank. For the ASP, how to price the services is a critical issue in winning the business, effectively delivering the service and remaining profitable. Typically, the price is bounded below by the cost of the service and above by the expected maximum the bank will pay. Determining that maximum and then negotiating a deal to extract the maximum gains is an art based on knowledge of the environment and the bank customer.

The art of pricing at ASPs, however, is highly variable and not well understood. In this study of 260 contracts from an application service provider, price discounts, measured as a discount from the vendor's standard price lists, range from 99.5% to 0% (full price is charged). This range of price discounting appears to be unique to IT services, and, to date, has not been examined in the IT field. Although some work has been done on IT contract structure (e.g., Ma and Seidmann, 2008; Gopal, L, Sivaramakrishnan, K. Krishnan, M. and T. Mukhopadhyay (2003).) and the relationship between prices and service quality contract terms (Domberger, Fernandez and Fiebig, 2000), ASP contracting and the determinants of price discounts has not been addressed.

It is crucial to understand how to set prices and how the contract structure (contract length, pricing structure, and other key terms) and bank characteristics affect the pricing. For ASP vendors, profitability depends on effective pricing. For banks, outsourcing success depends, at least in part, on controlling costs. For academicians, understanding the dynamics of the ASP (SaaS) market and how IT providers and banks interact is an open question. The factors affecting the price and contract structure, therefore, are of extreme interest to both practitioners and academicians.

This research specifically examines whether key factors such as bank size, sales person, the type of contract (fixed-fee versus variable), contract length, and incumbency affect the price discount an ASP gives, and if so, by how much? This paper proceeds as follows. The process of outsourcing to an ASP is described. The pricing and IT contracting literature are briefly reviewed, from which hypotheses are generated. A regression model to test these hypotheses is described, followed by a description of the data used. The results of the analysis are presented, and the paper finishes with a discussion and conclusion.

CONTRACTING PROCESS FOR ASP SERVICES

In general, the contracting process follows a common format, but also has significant variation in the interactions between the banks and ASP that are omitted from the following outline. A bank decides to possibly outsource its IT and selects a set of vendors to whom it sends a request for proposal (RFP). The set of vendors receiving the RFP is typically a small subset of the potential vendors. The vendors respond with their proposal for services and price. The bank reviews the proposals, selects a vendor and then negotiates a contract. This contract negotiation is a bilateral bargaining process where the expected gains from trade are split.

In this process, the bank wants to maximize Σ_{time} [v(service) – c(service)-c(switching) – c_{Bank}(contracting)], and the ASP wants to maximize Σ_{time} [p(service)-c(operations) – c_{ASP}(contracting)]. In this model, v(service) is the value to the bank of the IT services. The closer the services match the bank's needs, the greater their value. The cost to the bank is comprised of three components. The cost of the service itself, c(service), is the main component. If the bank contracts with an ASP, this will equal the price paid to the ASP vendor (p(service)). If the bank does not find a suitable vendor or does not like the contract terms, it can provide the IT services in house. In this case, c(service) is the internal cost to provide the IT services and p(service) is zero. This puts an upper bound on the price the ASP can charge for the service (alternatively a lower bound on the discount from its list prices it can give).

If the bank has already outsourced the service, one of the key considerations is the costs of switching to another vendor, *c*(switching). There is also a switching cost if the bank provides the service itself and switches to an ASP or uses an ASP and switches to in-house service provision. The switching costs are assumed to be zero (0) if the bank is using an ASP and continues to use that ASP to provide its IT services.

Both the bank and the ASP face contracting costs, c_{Bank}(contracting) and c_{ASP}(contracting), that include the cost of finding and selecting a vendor, negotiating the contract and monitoring the contract over its life. The ASP also has the cost to provide the services, *c*(operating). The marginal cost of processing a single, additional transaction is zero. The cost of adding another bank, however, is not. The key issue is whether the costs differ by bank. For the ASP examined, the Chief Operating Officer, COO, stated that there was no significant difference in the cost to provide service for its different banks. This may or may not be true, but since the COO was one of the executives that reviewed contracts before signing, his beliefs about the costs are what affect the ASP's willingness to accept a deal and hence the price the ASP charges.

The total gains from the deal are Σ_{time} [*v*(service) – *c*(switching) - c_{Bank}(contracting) - *c*(operations) – c_{ASP}(contracting)]. How much of these gains each party gets depends, in part, on their bargaining power. The size of the gains and each side's bargaining power will determine the price discount; therefore, the different components of the gains will affect price discounts. All else equal, higher *v*(service) implies more total gains to share and potentially higher prices (smaller discounts) – but *only* if the ASP knows *v*(service) and has the bargaining power to extract the gains. All else equal, *c*(switching) lowers total gains; therefore a firm switching to the ASP will likely have a higher discount. Similarly, c_{Bank}(contracting) and c_{ASP}(contracting) lower total gains, so would should result in lower prices (higher discounts).

Direct measures of these factors do not exist. Therefore, observable variables that affect or are related to these measures are used instead. These variables are drawn from both the literature and from examining differences in the contracts and differences among banks. The variables used are: incumbency, length of association, contract length, contract type, bank size, bank efficiency and sales person.

LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

Customer incumbency is a key factor affecting prices; although explanations for its impact differ based on the focus of the model. For incumbency to lead to higher prices, a firm must be able to segment its market between existing and new customers. The price differences can be driven by switching costs or by the ability to charge different customers based on how they value the service provided.

If there are switching costs – something believed to exist and affect pricing in IT (Varian, 2001) – existing customers will be charged a higher price than new customers (Farrell and Klemperer, 2006). In fact, new customers are given a discount to entice them to make an initial purchase and the expected discount increases with switching costs (Chen, 1997). After the initial purchase, the vendor raises prices in subsequent periods.

Even in the absence of switching costs, it can be optimal for firms to charge existing customers more than competitor's customers (Fundenberg and Tirole, 2000; Villas-Boas, 1999; Shaffer and Zhang, 2000). The goal is to poach the competitor's customers who only mildly prefer the competitor's product or service while charging a premium to the existing customers who strongly prefer the firm's product or service.

Empirical research shows incumbency affects prices in the newspaper, telephony and IT maintenance and support markets (Asplund, Eriksson and Strand, 2001; Epling, 2002; Domberger, Fernandez and Fiebig, 2000). Newspapers can identify existing customers, and new customers are offered a lower price than existing customers, but whether it is due to switching costs or customer poaching is not examined (Asplund, Eriksson and Strand, 2001). In the telephony market, individuals who are less willing to switch carriers pay significantly higher prices (Epling, 2002), and in IT maintenance and support contracts, customers renewing with their existing service provider pay more than those who switch vendors (Domberger, Fernandez and Fiebig 2000).

In the ASP market, vendors can identify existing customers, thus the vendor has information on the value of its services for client banks versus target banks. Additionally, there are switching costs. Switching from one vendor to another entails two possible costs. First, switching vendors requires converting the data from one vendor's systems to the other vendor's systems. Secondly, the users must be trained to use the new system, which leads to:

H1 Existing banks will have higher prices (smaller discounts) than new customers

If incumbents pay more, does the length of their incumbency affect the prices they pay? The length of incumbency is not typically a feature of economic models; so there is no theory to guide the discussion. There is, however, significant variation in the length of the incumbency among the banks, with the length of the association varying from zero (new customer) to 28 years.

The duration of incumbency may affect switching costs. In an ASP environment, the applications are not typically customized for the bank, which would require significant specific investments by both parties. They do, however, do some customization and create customized reports, and there is some specific investment in learning to work together. At the least, there could be psychological switching costs, which would imply that the longer the ASP-Bank relationship, the higher the prices the bank will pay. This leads to:

H2 The longer a bank has been a client, the higher the prices it will pay.

As with the length of the incumbency, contract length may affect prices. Using a long-term contract will reduce the average transaction costs associated with finding a vendor and negotiating a deal. Harris and Holmstrom (Harris and Holmstrom, 1987) show that a non-contingent upper bound to the length of a contract is optimal, but do not address the contract length's interaction with price. Fundenberg and Tirole (Fundenberg and Tirole, 2000) show that long-term contracts can affect the impact of incumbency. A firm (e.g., ASP) could prevent poaching by using a long-term contract, but it will always be better off using short-term contracts.

Empirically, long-term contracts are linked with uncertainty and with appropriation hazards. For well-head contracts, if a seller expected future contracts to be on less favorable terms it would opt for long-term contracts, but if future contracts were expected to be on more favorable terms, it would opt for short-term contracts (Crocker and Masten, 1988). With coal contracts, the potential for opportunistic behavior was associated with longer contracts (Crocker and Masten, 1988). Although they do not address pricing specifically, these studies imply that expected future prices are related to the use of long-term contracts, but there is not a link between the current price and the contract length. In IT maintenance and support contracts for hardware and software maintenance, longer term contracts were associated with a price premium (Domberger, Fernandez and Fiebig, 2000). Following the IT maintenance and support contract literature, leads to:

H3 Longer contracts will be associated with higher prices

Banks have a choice between bundled, fixed-fee contracts and per-unit contracts. With a fixed-fee contract, the firm is able to plan their expenditures, but not necessarily control them. Alternatively, if there is a per-unit contract, the monthly service cost will vary with usage, which does not necessarily correlate with the bank's revenue. A risk averse bank may prefer a fixed price contract and an ASP will offer one if it can charge a premium (this assumes the ASP is risk neutral), thus the choice of contract type may affect the price charged.

Empirically, the impact of contract structure is contradictory. For legal services, there is a price premium charged by firms using hourly rates for routine services (Smith and Cox, 1985). For IT maintenance services, no relationship was found between prices and contract structure (Domberger, Fernandez and Fiebig, 2000). Following the IT literature leads to:

H4 The pricing structure (fixed-fee or per unit pricing) does not affect price.

Bank size, salesperson and firm efficiency do not affect the size of the gains from trade, but may affect bargaining power. Empirically, research shows that customer size affects bargaining power, with larger customers receiving lower prices (Tyagi, 2001). In the ASP market, the bank may provide the service itself, internally. The ability to backward integrate limits the amount the ASP can charge. Since larger firms are more likely to have the resources to backward integrate, they have more bargaining power and should receive a lower price.

At the ASP studied, the sales person had significant leeway in pricing the deal. Research in marketing (Woodside and Davenport, 1976) show that the sales person can affect price and price elasticity. This does not address, however, how or if different sales people will consistently differ in their pricing decisions with some "giving away the farm" and others squeezing their bank for their last nickel. It also does not address the bank's ability to negotiate.

Since the final price is the result of a bilateral negotiation, if a sales person is a superior negotiator, it should show up consistently in the prices – especially since the sales person's compensation depends on the value of the deal. Alternatively, a bank that is cost conscience will likely put more effort into negotiating lower prices. Thus banks with lower expense ratios will like have lower prices. These lead to:

H5 *Larger banks will pay lower prices*
H6 *Sales person will affect price*
H7 *Banks with lower expense ratios will pay lower prices*

EMPIRICAL MODEL

Multiple regression enables the comparison a large number of contracts while controlling for relevant information that may rationally affect price. It has been used in previous studies to examine the existence of price discrimination (Ladd, 1998) and to identify the factors affecting bargaining power and therefore price discounts (Sorensen, 2003). To test these hypotheses, we use a regression model where the discount provided is a function of the firm, vendor and contract characteristics. Specifically:

$$P = \alpha + \beta_1 I + \beta_2 IL + \beta_3 CL + \beta_4 CT + \beta_5 S + \beta_6 SP + \beta_7 E + \varepsilon \qquad (1)$$

Where:

Table 1: Model Parameters

Variable	Description	Hypothesis
P	is the percent of list prices paid by the bank. It is calculated as the amount charged divided by the expected charges at full price	---
I	Represents incumbency and is a binary variable indicating whether the contract is a renewal or a new bank	H1
IL	If the contract is a renewal, IL is a measure, in days, of how long the bank has been serviced by the vendor	H2
CL	Contract length measure in months	H3

Table 1: Model Parameters		
Variable	Description	Hypothesis
CT	Binary variable for contract type indicating whether the contract is fee for service or fixed fee	H4
S	Size of bank measured as assets, employees, sales or number of accounts in a key master file (which is also a measure of the amount of business done between the bank and ASP)	H5
SP	Sales person	H6
E	Bank efficiency measured as revenue/asset, revenue/employee, cost/employee	H7

We use this model to test hypotheses the hypotheses. A significant parameter coefficient with the appropriate sign indicates support for the hypothesis.

DATA

Most of the data in this data set is unique and proprietary. It is summarized in -Table 2. It includes information from 260 contracts and invoices tied to those contracts. The contract data includes the services provided, key pricing terms, length of contract, and how long the bank had been a client of the ASP. The invoices include the quantities of these services used, the list price and actual price charged. Some contracts bundled these services together and charged a fixed fee for the services. That data is also included. Because of the sensitive nature of the data, the ASP that provided the data has asked that anything that could be used to identify it or its client banks be disguised. This has been done where it would not affect the results of the analysis. The data included the name of the sales person as well as information on the banks, including a copy of their financial statements.

Table 2: Summary Statistics						
Variable	Obs	Count	Mean	Std. Dev	Min	Max
Percent of List Price	260		0.701535	0.253306	0.005399	1
Contract is a Renewal	260	129	0.498039	0.500979	0	1
Days with the Vendor	260		2820.035	2263.035	14	11446
Contract Length	260		60.0549	13.55032	12	120
Per Unit Priced Contracts	260	121	0.47451	0.500332	0	1
Salesperson 1	260	24			0	1
Salesperson 2	260	15			0	1
Salesperson 3	260	13			0	1
Salesperson 4	260	14			0	1
Salesperson 5	260	7			0	1
Salesperson 6	260	5			0	1

Table 2: Summary Statistics

Variable	Obs	Count	Mean	Std. Dev	Min	Max
Salesperson 7	260	23			0	1
Salesperson 8	260	16			0	1
Salesperson 9	260	15			0	1
Salesperson 10	260	5			0	1
Salesperson 11	260	19			0	1
Salesperson 12	260	4			0	1
Salesperson 13	260	22			0	1
Salesperson 14	260	7			0	1
Salesperson 15	260	29			0	1
Salesperson 16	260	8			0	1
Salesperson 17	260	22			0	1
Salesperson 18	260	12			0	1
Number of Accounts	260		29810.64	39471.12	302	366023
Assets	260		295489.9	442587.1	9053	3447366
Number of Employees	260		86.49804	129.4192	3	1138
Revenue	260		22601.13	32856.13	503	232730
Asset efficiency	260		0.026758	0.012185	0.008829	0.207317
Employee efficiency	260		80.71005	22.85175	41.84211	213.776
Revenue efficiency	260		0.346449	0.17926	0.125276	1.848771

The key dependent variable is the percent of list price paid by the bank. This is calculated by dividing the actual invoice amount charged the bank by the value of the services used at list prices. Since the ASP provided both a price list and an invoice that specifies actual usage as well as amount charged, calculating the discount was simple. The invoices cover one month of service. The value of services at list prices ranged from $500 to $380,000 and averaged $44,270. Total cost paid as a percentage of list ranged from .5% to 100% (full prices) and averaged 71%.
The vendor's contract documentation includes when the bank first started using the vendor as well as when the most recent contract was signed. If the original contract date was earlier than the most recent contract date, the bank was coded as an incumbent. 50% of the banks were incumbents. The length of time the firm had been a bank was measured in days and equaled the current contract date minus the original contract date. The length of incumbency ranged from 14 (for a new bank) to 11,466 days. For incumbents, the average length of incumbency was 4,130 days.

The contract length was coded in months and ranged from 12 to 120. Thirty contracts were less than sixty months in length, 192 were sixty months long, and thirty eight were longer than sixty months.

Different measures of bank's size were evaluated including: assets, revenues, and number of employees. The first two measures were taken from the bank's financial statements. The third measure was provided by the bank. These variables are highly correlated (0.9582 between assets and revenues), so only one was included in the model at a time. A somewhat different measure of size is the number of accounts in a key master file. While measuring size, it also measures the amount of business being done between the bank and the vendor and was taken from the ASP's records.

Different measures of bank efficiency and their cost consciousness were evaluated. The measures included operating costs in dollars/assets in dollars (asset efficiency), operating costs/number of full-time employee equivalents (employee efficiency) and operating costs/revenue (revenue efficiency). Full-time employee equivalents equals the number of full-time employees plus ½ the number of part-time employees. These measures indicate how efficiently the organization uses its resources and its cost consciousness.

A set of 18 binary sales person variables were used. If sales person 1 was identified as the sales person on the most recent contract, then the variable was coded as a 1; otherwise it was coded as 0. 26 different sales people were involved in the 260 contracts. In 9 cases, the sales person had fewer than 4 sales. All sales people with fewer than 4 sales were combined and coded as "sales person 18".

RESULTS

The model was highly significant (F(7,253)=71.62) with an R^2 of .40. The model was constructed to minimize multicollinearity. Where multiple measures of the same construct were possible, such as firm size, only one was included in the model at a time. The model was rerun with each size variable and with each efficiency variable and the best model was selected. The largest correlation between the remaining variables was .586 between renewal and days with vendor, but the variance inflation factor (VIF) was only 1.69, and the average VIF was 1.27. The Ramsey reset test indicated that non-linear transformations of the variables have not been omitted (F= 0.79). The Breusch-Pagan/Cook-Weisberg test showed heteroskedasticity is present (Chi(1)=16.81), so heteroskedastic robust error terms were used to test for parameter coefficient significance.

Table 3: Regression Results

Variable	Coefficient	Standard. Error	t-value	P>|t|	Significance
Incumbency (contract is a renewal)	0.091068	0.034403	2.65	0.009	***
Length of incumbency (in days)	5.60E-06	6.37E-06	0.88	0.38	
Contract length in months	0.000233	0.000689	0.34	0.736	
Fixed fee contract	0.241533	0.03048	7.92	0	***

Table 3: Regression Results					
Variable	Coefficient	Standard. Error	t-value	P>|t|	Significance
Employee efficiency	9.84E-05	7.38E-06	13.33	0	***
Sales person 6	0.25097	0.122734	2.04	0.042	***
Log of Number of Accounts	-0.03558	0.013381	-2.66	0.008	***
Constant	0.853964	0.14226	6	0	***
Number of obs = 260					
F(7, 252) = 71.62					
Prob > F = 0.0000					
R-squared = 0.40					

Five of the model's seven parameters were significant at the .05 level of significance or better (see table 3). The coefficient for the incumbency variable is positive and significant (0.091; p-value=.009). This implies that firms renewing with the ASP pay a higher percentage of the list price than do similar firms negotiating a new contract, so there is third degree price discrimination based on incumbency. The size of this premium is significant – 9.1%, so an incumbent firm with a monthly invoice of $10,000 would pay $910 more than a similar, newly signed bank.

Bank size measured by assets, revenues and number of employees was highly correlated with the number of accounts. Using the number of accounts provided the best model. Larger customers – at least those that do more business with the ASP measured by the number of records in a key master file – pay a smaller percentage of list prices. The coefficient for the lnaccount parameter is negative and significant (-0.0356; p-value=.008). Lnaccount values range from 5.7 to 12.8 and averaged 9.763, so, all else equal, the firm doing the most business with the vendor pays about11 percent of list less than the average sized bank. This confirms that firms doing more business with the ASP have more bargaining power, which echoes Sorensen's findings when studying bargaining power between hospitals and insurers (Sorensen, 2003).

The payment structure – fixed fee versus per unit prices – also significantly affected the percent of list paid. The coefficient for fixed fee contracts was positive (0.2415; p-value = 0.0) indicating that banks with fixed fee contracts pay a premium. This appears to be third degree prices discrimination based on contract type preferences. There is no indication that customers selecting this type of contract are more expensive to serve, and discussions with the vice president of operations support this conjecture.

Finally, the positive and significant coefficients for both the sales person and the employee efficiency parameters imply that bargaining ability matter. The price charged the bank depends on the sales person's ability to negotiate a better deal for the vendor, and the bank's ability to negotiate a deal for itself. It is interesting to note that the coefficient for only one sales person was significant. To verify this, each sales person was included by itself and with the significant sales person, and only sales person 6 was significant. The employee efficiency parameter (0.0001, p-value = 0.0) is positive, so operational efficiency (lower operating costs per employee) does translate into better bargaining. The impact, however, is small, with the difference in percent of list prices between the average employee efficiency and the best (lowest) employee efficiency being only .004.

Finally, the length of the incumbency (.000006; p-value = .38) and the length of the contract (.00023;p-value=.736) had no effect on price, so both hypotheses *H2* and *H3* are not supported.

FURTHER ANALYSIS

The initial analysis shows that four of the six hypotheses are supported. Two of these – the impact of incumbency and the impact of the contract type – are binary and subject, given the data set, to further analysis. In particular the interaction among the incumbency variable and other variables as well as the interaction among contract type and the other variables was analyzed. To conduct the analysis, two additional regression models were constructed. In the first additional regression, interaction variables between incumbency and time with vendor, contract length, contract type, bank size, sales person, and bank efficiency were added, giving:

$$P = \alpha + \beta_1 I + \beta_2 IL + \beta_3 CL + \beta_4 CT + \beta_5 S + \beta_6 SP + \beta_7 E + \beta_8\, IL\cdot I + \beta_9 CL\cdot I + \beta_{10} CT\cdot I + \beta_{11} S\cdot I + \beta_{12} SP\cdot I + \beta_{13} E\cdot I + \varepsilon \qquad (2)$$

In the second additional regression, interaction variables between contract type and incumbency, time with vendor, contract length, bank size, sales person, and bank efficiency were added, giving:

$$P = \alpha + \beta_1 I + \beta_2 IL + \beta_3 CL + \beta_4 CT + \beta_5 S + \beta_6 SP + \beta_7 E + \beta_8\, IL\cdot CT + \beta_9 CL\cdot CT + \beta_{10} CT\cdot I + \beta_{11} S\cdot CT + \beta_{12} SP\cdot CT + \beta_{13} E\cdot CT + \varepsilon \quad (3)$$

Because the number of observations for salesperson 6 was low, the interaction terms related to sales person 6 were dropped. Both models were highly significant (Model 2: F(12, 247)=46.9 and Model 3:F(12, 247)=49) with an R^2 of .40 and .41 respectively. In neither case was the full model was significantly better than the reduced model (for model 2 chi(5) = 3.02 with Prob > chi^2 = .69. for model 3, chi(5) = 7.61 with Prob > chi^2 = .1792). This implies that incumbency and of the contract type directly affect the price and the effect is consistent for all banks.

SUMMARY AND CONCLUSIONS

This research examined data associated with 260 contracts between and ASP and its banks to assess the factors affecting the price discount given to the banks. Following economic theory, incumbency and bank size affect the price discount. The economic theory, however, does not address the relative importance of these factors, or does it address other factors such as contract type. In this study, contract type had more than twice as large an impact on the price discount than did incumbency (0.24 vs 0.09). This greater impact of contract type implies that bank identification is more important to profitability than signing banks and exploiting the incumbency at contract renal time.

By offering a contract that fixes the monthly fee for a year, the ASP is able to charge those banks a significant premium at little risk to itself. The amount charged is changed each year based on usage, so the ASP has little down-side risk. Additionally, since the bank does not control usage (its customers do), it cannot game the system. This enables the ASP to generate approximately 12.6 % per year in additional revenue (52.55 percent of banks with a fixed-fee contract * 24 % premium for fixed fee).

The largest banks pay 9% of list price less than the average bank, and about 25% less than the smallest banks. Size, thus confers a significant price advantage. Even though the marginal cost of serving different sized bank does not differ significantly. Large banks may even argue that they are paying a premium. Consider an average bank with 17,300 accounts (lnaccounts = 9.76) and a large bank with 360,000 accounts (lnaccounts = 12.81). The average bank will pay 51 % of list (assuming it has a per unit contract and is a new bank). The large bank will pay 42 % of list (also assuming it has a per unit contract and is a new bank). If the list is $1.00 per account, the large bank pays $151,000 per month versus $9,000 for the average bank – which they could see as a $142,000 premium.

Two other factors, not typically addressed by economic theory, that affect the prices are the sales person and the bank's efficiency. Only one of the eighteen salespeople consistently affected the price charged. That sales person consistently extracted higher prices from his or her banks than did the other sales people. The sales people have significant latitude at the ASP studied. They are also paid commission, so they have an incentive to get higher prices, but not at the expense of losing a bank. There is not data on lost banks and potential banks not signed to determine whether sales person 6 drove away business and should be replaced or extracted additional rents and should be emulated.

Firms with lower operating cost per employee – those that are in one sense more efficient – also pay a lower percentage of list prices. It is possible that there is a tautology. The lower price lowers operating costs, which lowers operating cost per employee. Alternatively, firms concerned about operating costs bargain harder and get a better deal. Note that if employee efficiency is correlated with profitability, then these results are the opposite of what is found in wage bargaining (Mishel, 1986), where an ability to pay is liked to higher wages.

For companies considering outsourcing or continuing to outsource to an ASP, the existence of price discrimination has implications for management outsourcing to an ASP. The price they pay will depend on how well they negotiation their contract. Since they can expect to pay more when they renew their contract, they may want to negotiate a longer deal. They also need to carefully consider whether having a fixed, predictable monthly fee is worth the increased price that accompanies it. It may be less expensive to spend time forecasting usage and negotiating a per-unit contract. Finally, larger banks need to leverage their size to obtain significant discounts.

As with all research, this study has limitations. The data was collected from only one vendor. This raises the possibility that the results are unique to that one vendor. To address this, we contacted a competitor to the ASP vendor that provided the data and asked them about their contracts. This vendor also negotiates the terms of each contract with each bank. It has both fixed fee and per unit pricing and gives discounts to some of its banks, so the structure of the deals is similar.

The banks for the study were also all in the same industry and were all of similar size (relatively small). This removed some variability from the data, but also limits whether the results can be generalized to other industries and to large banks. Even with these limitations, this research makes a significant contribution to the understanding of the relative importance of key factors affecting ASP pricing.

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