Charter Flips by National Banks

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Abstract

Bank management can change its charter and so its supervisor(s) at any time. Some argue that the supervisory competition resulting from the existence of the charter flip option promotes more efficient bank regulation. Others assert that it leads to "competition in laxity" as supervisors compete for clientele. Research on this issue is warranted because little empirical research on charter flips is available and the frequency of flips appears to have risen during the past decade.

This paper focuses on identifying the factors that best explain the decision of national banks to convert to a state charter. A discrete-time logistic hazard model is used in the study. The sample consists of 2,298 national banks followed quarterly over the 1994 – 2001 time period. The results reveal that several indicators of bank risk significantly increase the likelihood of a national bank charter flip. The opposite effect is evident for a measure of credit risk. The results also indicate that flips are more likely, the more competitive the local market in which a bank operates and in states where past flip activity has been high. Several supervisory variables also are significantly related to the likelihood of charter flips, even after including the effects of the set of variables previously discussed. In general, banks are more likely to flip their charter the worse their supervisory ratings, although the relationship is non-monotonic.

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Charter Flips by National Banks

I. Introduction

In general, the management of any operating banking organization can change its charter (or the charters of multiple bank affiliates) and so its supervisor(s) at any time. A number of possible reasons exist for bank charter switching. Bank management may elect to change charters to improve its desired risk/return profile. Charter changes might result in lower explicit or implicit supervisory costs. Different charters may also permit the exercise of different powers. Since supervision is inherently somewhat subjective and supervisors can differ in their approach or attitude, banks might change their charter in the hope of obtaining a more "compatible" supervisor. Alternatively, supervisors might push problematic banks or pull healthy banks to flip charters. Environmental forces could also put performance pressures on banks that serve as a necessary catalyst for charter changes.

The existence of a charter flip option has a number of implications for both banks and their supervisors. For example, the flip option may result in more efficient supervision over time by stimulating desirable competition among alternative regulators, whose budgets, reputations, or ability to achieve multiple goals are linked to the number and size of the institutions they supervise. Charter flips might also facilitate risk-taking by banks. This might happen if it takes time for new supervisors to evaluate switching banks or if old supervisors "push" riskier banks to flip. The option to flip might also result in excessive supervisory competition and overly lax supervision. Since the number and size of converting banks appears to have increased during the 90s, a better understanding of the motives for charter change is desirable. Little empirical work on this issue has been done to date.

This paper focuses on identifying the factors that best explain the decision of national banks to flip to a state charter. This sort of charter change, as opposed to state banks switching their primary federal supervisor, is analyzed for several reasons. One is that the net benefits of flips from a national to a state charter are likely to be more pronounced and have potentially more varied causes.[1] The other is that focusing on national banks allows supervisory information to be used in the analysis. A discrete-time logistic hazard model is used in the study. Hazard models offer advantages over alternative static techniques when analyzing phenomena like charter flips. The sample consists of 2298 national banks, followed over the 1994 – 2001 time period. A quarterly time horizon is used in the analysis.

Briefly, relatively few bank financial variables were found to be significant predictors of national bank charter flips. The results do generally suggest a positive relationship between bank risk and the likelihood of a charter flip. However, higher values of nonperforming loans ratio significantly reduce the probability of a charter flip, possibly because this loan quality ratio is viewed as a more contemporaneous, clearer signal of the magnitude of a bank's credit risk than other risk measures, and as such might raise supervisory concerns about the motives for or potential costs of a bank flip. The estimation results also revealed that MBHC lead banks are more likely to flip, ceteris

[1] For example, roughly 88 percent of the supervisory flips by state banks that changed their primary federal supervisor from the FRB to the FDIC or vice versa over the 1990 – 2001 period went from the FDIC to the FRB. This trend suggests that most of these shifts are motivated by a simple desire of bank holding company management to eliminate one federal supervisor.

paribus, but this propensity decreases the higher the percentage of consolidated holding company assets in national bank subsidiaries.

Several environmental variables had significant coefficients in the charter flip model. These findings suggest that more intense competition increases the likelihood of flips. The lagged national bank flip rate was also found to be significantly and positively related to the likelihood of a charter flip. This finding presumably reflects the existence of, and competitive pressures attributable to, advantages associated with state charters.

Supervisory variables are significantly related to the likelihood of charter flips, even after including the effects of the set of variables discussed previously. Empirical support was found for a quadratic relationship between composite CAMEL ratings and the likelihood of a charter flip. Formal enforcement actions also increase the likelihood of a flip. Finally, less favorable management (M) ratings by supervisors also increase flip likelihoods.

A limited examination of forecasting accuracy reveals that the estimated models were only modestly successful in identifying converting banks. This might be due to the quarterly data used in the analysis.

The rest of the paper is organized as follows. The next section contains a review of the only existing study of the factors influencing bank charter flips. The data and sample are discussed in the third section. This is followed by a discussion of the model and explanatory variables. The estimation results are detailed in the fifth section, which is followed by a discussion of forecasting accuracy and finally the summary and conclusions.

II. Previous Research

Rosen (2002) is the only recent empirical study exploring the determinants of bank charter flips.[2] In this paper, the author focuses on the factors influencing banks to change their primary federal supervisor over the 1983-1999 period. He emphasizes two possible motives for such a change. One is a desire by bank management to move to a more preferable risk/return tradeoff. This leads him to use measures of bank risk and return as explanatory variables in his estimated model. The other suggested motive is pressure on problematic banks to flip by current supervisors who desire a "quiet life." He does not use supervisory data to develop a measure of this pressure. Instead he assumes that supervisors consider banks that change the composition of their loan portfolio a great deal, hold more difficult-to-evaluate assets, or are riskier to be problematic. His indicator of portfolio change is the sum of the absolute value of the loan portfolio shares of seven different categories of loans.[3] He expects this variable and the probability of a charter switch to be positively related.

He estimates several different simple logit models of supervisory flips. First he estimates several alternative versions where banks of all initial charter types are pooled and the dependent variable takes on a value of one for banks that change their primary federal supervisor within a given year, otherwise it is equal to zero. He also estimates separate models for banks that switch from, and then to each type of federal supervisor. His explanatory variables in all cases include measures of bank size, his loan portfolio

[2] See Rosen (2002). This paper also explores performance changes after charter flips. Since this issue is not explored here, that portion of Rosen's paper is not discussed.

composition change variable, several measures of bank risk and return (equity/assets, total loans/assets, nonperforming loans/total loans, return on equity), a merger dummy, holding company lead bank dummy, several nonlead holding company affiliate dummies (controlling for charter differences relative to the lead bank), existing supervisor dummies, and year dummies. He uses a variety of transformations of the non-dummy explanatory variables, including levels, changes in levels, and dummy variables based on upper and lower quartile values, arguing that these variables may be non-monotonically related to the likelihood of a supervisory change. None of his models include any environmental variables or explicitly take censoring or possible duration dependence into account.

He estimates his model using pooled annual data over the 1983-1999 period. Thus the lag between the point in time at which his explanatory variables are measured and his sample banks flip can vary from 0 up to 12 months. This substantial variation could influence his reported results.

When he estimates equations in which he does not distinguish between types of supervisory flips, he finds that banks are more likely to switch if they have merged, are within a holding company, are performing poorly, or are larger.[4] In fact, he notes that much of the explanatory power of the estimated equations comes from the merger and holding company structure variables. The other explanatory variables generally are significant only when he uses quartile dummies as opposed to continuous versions of the variables. He emphasizes the significant coefficients on the loan portfolio change

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[3] The categories are construction loans, commercial real estate loans, mortgage loans, other real estate loans, commercial and industrial loans, consumer loans, and other loans.
[4] These results are reported in table 4 in his paper.

variables (both continuous and the dummy quartiles) is his conclusion that the results basically provide support for the "quiet life" motive for supervisory change.

He also re-estimates separate logit equations in which the dependent variable is set equal to one for banks that change to or from each type of primary federal supervisor. The specifications of these equations are basically the same as those used for the pooled sample. Focusing on his most relevant equation for the purposes of this study in which he explores the determinants of the probability that national banks surrender their charter, he finds few significant predictors of flips.[5] His size variable and his four key financial variables measured in levels are all insignificant. He does find some significant change in quartile dummies based on these four ratios. The coefficient on the change in loan-to-asset ratio bottom quartile dummy is positive and significant. A similar result is evident for the change in nonperforming loan ratio bottom quartile dummy. He interprets these findings as consistent with his quiet life hypothesis, since they imply that flips are more likely when risk is changing in either direction. He also finds a positive significant coefficient on the change in return on equity top quartile dummy.

He gets significant coefficients on his upper and lower quartile portfolio change dummies (positive and negative, respectively) and interprets these findings as additional support for his hypothesis that supervisors desire the quiet life. In fact, he emphasizes the empirical support for this hypothesis in this and the other models estimated as the main result in his paper.

It is not clear that this interpretation is accurate. The loan portfolio composition measure is likely to be a poor indicator of the difficulties involved in supervising a bank. This is true for such a measure in general and the specific variation that is used in the paper. The job of supervisors is the easiest at banks that are financially the strongest, and supervisors would prefer all banks to be so. Financial strength is likely to be correlated weakly with changes in loan portfolio composition in general. The measure used in the study weights each of the seven loan categories equally. It is unlikely that changes in loan portfolio composition attributable to mortgage loans or consumer loans have the same supervisory implications as changes in construction loans. Further, this interpretation of the reason for the observed relationship between the loan composition variable and the probability of a charter flip fails to recognize that the revenue sources and the incentives of supervisors differ across the three federal agencies. Only one of the three federal bank supervisors (the OCC) derives its revenues from the banks it supervises and so its examiners may be most inclined to temper a desire for the quiet life with concerns about future funding. Yet despite the obvious differences in supervisory incentives, the estimated coefficients have the same sign and statistical significance for both the national bank and state nonmember bank subsamples and are even very close in absolute size. This suggests that this variable may actually be serving as a proxy for something else.

III. Sample/Data Issues

The 2298 national banks in the initial sample are a subset of all national banks in existence as of December 31, 1993. National banks in existence less than three full years as of this date and all credit card banks were excluded from the analysis.[6] The sample

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[5] This equation appears in table 8 in his paper.
[6] Credit card banks are defined as banks with consumer loans equal to 75 percent or more of total assets.

also excludes nonlead national bank MBHC affiliates.[7] The reason for this exclusion is as follows.

Charter flips at the bank level clearly reflect the independent, voluntary decision of its management for one-bank holding company (OBHC) subsidiaries or independent banks (IB). Thus, the likelihood of such banks converting should be related to the financial and environmental conditions of that bank. This is also likely to be the case for the lead bank affiliates of multibank holding companies (MBHC), but not for the nonlead affiliates. The management of the parent company, typically the same as that of the lead bank, is likely to decide the number and charter types of the nonlead affiliates. So the flip decisions of nonlead bank affiliates is not likely to reflect their respective financial and environmental conditions, but rather that of the consolidated entity. As a result, it seems appropriate to exclude nonlead MBHC affiliates from a bank level study of the determinants of bank charter flips.[8]

The sample also excludes banks that switched into the national banking system from January 1, 1991 through December 31, 1993. The reason for dropping these banks is that multiple charter switches by banks are relatively rare, so the likelihood of another change by recent converts is fundamentally different from the other banks in the sample with otherwise similar characteristics.

These exclusions resulted in an initial sample of 712 independent banks, 1300 OBHC subsidiaries and 286 lead bank affiliates of MBHCs, observed over a maximum of 32 quarters. A total of 110 of the sample banks ultimately flipped out of the national

[7] Here each MBHC's lead bank is defined as the largest subsidiary in terms of total assets.
[8] This reduces the number of banks flipping out by 64 for this time period.

banking system over the entire period.[9] The number of sample banks that flipped each quarter over the interval examined appears in table 1.

A quarterly time horizon is used in this study. That is, the likelihood of a bank flipping its charter during a given quarter is assumed to depend on a variety of factors measured at the end of the previous quarter. The choice of this time horizon is admittedly arbitrary. But some amount of arbitrariness is unavoidable because the precise time lag between the unobserved point in time at which the charter flip decision is made by bank management and the time at which the switch occurs is unknown. At any rate, a quarterly time horizon appears to be preferable to an annual horizon, since it more closely links the timing of charter flips and their potential determinants. The quarterly time horizon also greatly expands the amount of information available to estimate the model.

The initial sample of banks is followed from the end of 1993 through the end of 2001. This implies that the origin of event time in this hazard analysis is January 1, 1994. Choice of the time origin is important in hazard analysis, since it can make a possibly substantial difference in coefficient estimates and the fit of the estimated model. It might be argued that a more appropriate time origin for this analysis would be the date at which a bank starts operation or the date at which it becomes "mature," since these are points in time when banks become exposed to at least some of the set of factors that influence the risk of a charter flip event. The origin used here was chosen for several reasons. One is that charter flips in general are rare and the time lag from bank birth to flip appears to be

[9] This total excludes banks that flipped their charter in the same quarter in which they were acquired by a bank holding company. Such banks are treated as censored instead.

long and variable.[10] This would make an analysis that defines the origin of event time as the chartering date of new banks problematic even if annual data are used. It also suggests that the risk of a flip is not merely a function of bank age.

Available data suggests that the incidence of flips has risen in the nineties.[11] One plausible explanation for this trend is an increase in the intensity of competition faced by banks in the wake of the removal of the remaining restrictions on interstate banking and branching culminating in the Reigle-Neal Act.[12] Thus the time period examined roughly coincides with the post-branching restriction period. The implicit assumption made here is that this time origin has the strongest effect on the charter flip hazard.[13]

IV. The Model and Explanatory Variables

The charter flip decision is analyzed using a discrete-time logistic hazard model.[14] This model has been shown to be a discrete approximation to the Cox proportional hazard model.[15] For the discrete logistic hazard model, the general expression for the likelihood of a charter flip for a representative bank i at time t is given by equation 1 below:

(1) $p_{i,t} = p(y_{i,t} = 1) = [1 + (1/\lambda)\exp(-c(t))]^{-1}$

where $p_{i,t}$ = the probability of a flip by bank i in period t

$y_{i,t}$ = 1 if bank i flipped its national charter in period t, otherwise equal to 0

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[10] For example, the mean and median age of the sample banks that flipped their charter were 61.5 years and 67.9 years, respectively at the time of the flip.
[11] See the annual flip data in Rosen (2002), table 2.
[12] For empirical evidence on the performance effects of branching deregulation, see Jayaratne and Strahan (1997).
[13] See the discussion concerning the choice of the time origin in Allison (1995), pp. 22 – 25.
[14] For other recent examples of the use of discrete logistic hazard models, see Shumway (2001), Gross and Souleles (1999) and Lundstedt (1999).
[15] See Shumway (2001).

$\lambda = \exp(X_{i,t-1}B)$

$c(t)$ = the baseline hazard function.

The baseline hazard function can be any of a number of transformations of event time. Typically, modelers employ linear, logarithmic, or polynomial functions of time and this is the approach taken here.

Some insight on the appropriate form of the baseline hazard function can be gained by examining non-parametric estimates of the hazard function. Life-table estimates of the empirical hazard rates are shown in Figure 1.[16] The graph shows that the hazard rates first fall and then rise, suggesting that the baseline hazard is non-linear.

Previous users of discrete-time hazard models cite a number of potential advantages relative to static binary dependent variable alternatives. One is the fact that the model explicitly controls for each sample bank's period at risk. It also permits the use of explanatory variables that vary over time. It also might permit more efficient out-of-sample forecasts.

The data set is basically an unbalanced panel consisting of bank-quarter observations in an event-history format. The value of the dependent charter flip variable is set equal to zero for each sample bank in each quarter it operates and does not flip its charter. The dependent variable takes on a value of 1 for banks that flip in the quarter in which they give up their national charter. Banks that do not flip are censored either at the end of the sample period or when they cease to operate for other reasons (e.g., merger or

[16] For a discussion of the life-table method, see Allison (1995), pp. 41-48. The empirical hazard rates in the table are defined for 4-quarter intervals of event time, plotted at the interval midpoints. The hazard rates represent the number of events that occurred over each interval divided by the number of sample banks "at risk." The number "at risk" in each interval is the number of banks remaining in the sample at the start of the interval minus the sum of the number of flips and banks censored over the interval divided by 2.

failure). The dependent variable in each time period is related to values of the explanatory variables measured at the end of the previous period.

The variables used in the study as predictors of the likelihood of a bank surrendering its national charter fall into three broad categories. One consists of various financial condition ratios and other institution-specific variables constructed from FDIC reports of income and condition and the Summary of Deposit file. These variables are indicators of bank risk, portfolio composition, rate of return, size, organizational structure, and previous merger activity. These variables typically change quarter-to-quarter for banks that remain in the data set. Given the time horizon used in the study, all items from the income statement used in the financial ratios are annualized quarterly figures.[17] In addition, since quarterly data can be relatively noisy, ratio values above the 99th percentile or below the first percentile are set equal to their closest boundary percentile value.

Predicting the effects of a number of these variables on the probability of a charter flip is difficult for several reasons. In some cases, a variable clearly reflects a single dimension of bank performance, but the relationship between this dimension of performance and the probability of a charter flip is not clear. For example, it is likely that the relationship between various measures of risk and the likelihood of a charter flip is generally positive, although it might not be linear or hold for measures of all types of risk. This positive relationship might be observed because higher risk banks favor even higher risk-higher expected return strategies and believe that changing supervisors would facilitate such a plan. This might occur because a different supervisor has a different

[17] As an alternative, averages of these ratios calculated over the previous four quarters were also used. The results were qualitatively the same.

approach or risk tolerance or is at least initially at an informational disadvantage. Also higher risk banks might be more likely to have had a contentious relationship with their current supervisor and so be interested in starting over with a new supervisor and a clean slate. Current supervisors might also encourage higher risk banks to flip. However, prospective supervisors might not permit obviously high risk banks to obtain new charters. Supervisors might also be more concerned about, or more consistent and accurate in measuring certain types (e.g., credit risk) of risk, reducing the likelihood that banks with higher levels of this sort of risk successfully switch their charter.

In other cases, a variable may reflect several dimensions of performance each with its own potential effect on the likelihood of a flip. For example, a lower gross yield on a loan portfolio could be interpreted as an indicator of a charter-related competitive disadvantage (binding legal lending limits reduce the amount and profitability of the loan portfolio) or could indicate a relatively safe loan portfolio.

Several ratios were used as alternative proxies for bank risk. These included equity divided by assets (EAAR), net capital (equity plus loss reserves minus noncurrent loans) divided by total assets (NCAPR), loans 30-89 days past due but still accruing relative to total assets (NP89LR), total noncurrent loans relative to total assets (NCLR), total nonperforming loans relative to total assets (NPLR), total insider loans relative to total assets (INSDLR) and the total loan to asset ratio (LAR).[18] Higher values of the first two of these ratios imply lower risk. The opposite is true for the other four ratios.

Several balance sheet ratios were also used as crude indicators of interest rate risk. Three different ratios were used: securities that reprice or mature in five or more years

[18]NCLR is defined as the sum of loans past due 90 or more days but still accruing plus nonaccural loans divided by total assets. NPLR is NCLR + NP89LR.

relative to total assets (SGT5R), loans that reprice or mature in five or more years divided by total assets (LGT5R), and the sum of these two ratios (TAGT5R).

Several other portfolio composition ratios involving loans were also considered as potential explanatory variables including commercial loans relative to total assets (COMLR), total "wholesale" loans as a percent of total assets (WSLAR), total consumer loans divided by total assets (CRLR), and total home equity and second mortgage loans relative to total assets (HE2MLR).[19] The first two ratios are intended to capture banks that might consider converting because of concerns about legal lending limit constraints. Legal lending limits were more liberal for state chartered banks than for national bank peers in a number of states over this period and allegedly convey a competitive advantage to beneficiaries. As a result, national banks more heavily involved in commercial or wholesale lending might be more likely to flip charters.

The consumer loan ratio and to a lesser extent the home equity-second mortgage ratio were intended to signify banks that might prefer the uniform nationwide consumer lending rules that come with a national charter. Accordingly, higher values of these ratios should be negatively associated with the likelihood of a charter flip. However, the latter ratio might also proxy for the extent of sub-prime lending and so be another indicator of loan portfolio risk. If so, the relationship between this variable and charter flip probability is unclear.[20]

Several ratios involving income statement items were also employed. Since banks flipping charters often cite the cost benefits of such a move, the ratio of noninterest

[19] The numerator of WSLAR includes commercial and industrial loans, commercial real estate loans, and agricultural loans.
[20] Simple correlation analysis reveals a positive significant correlation between HE2MLR and the broader credit risk ratios like NPLR.

expenses to net revenue (NONIER) was tried as an explanatory variable. The expected sign of this variable is positive.

Pre-tax ROA (PTROA) and ROE (PTROE) were also used in the analysis. Assuming that banks switch charters to enhance their performance, the expected of both of these variables is negative.

The gross yield on loans (GLYLD) was also employed as an explanatory variable. The expected sign of this variable is unclear a priori. It might indicate sub-par loan returns resulting from charter-related lending limit disadvantages. If so, the sign of this variable should be negative. Alternatively, it might proxy loan portfolio risk. The nature of the relationship between higher loan portfolio risk and the likelihood of a charter flip is unclear.

Finally, the ratio of noninterest income net of deposit service charges to net revenue is used as a proxy for the extent a bank is involved in less traditional lines of business (RNONIIR). The expected sign of this variable is unclear. If a national charter facilitated bank involvement in nontraditional activities during this time period, the expected sign of this variable should be negative.

Several other variables were drawn from call reports and attached structure files. This includes the log of total assets (LASSET) as a measure of bank size, and the number of mergers in which a bank was involved over the previous four quarters (NM4Q). The relationship between size and the probability of a charter flip is unclear. Since mergers involving the sample banks imply the possibility of a combination with a state bank, the number of mergers and the probability of a charter flip are likely to be positively related.

Since some MBHC affiliates are included in the sample and the characteristics of the MBHC might also influence the probability of a charter switch, two additional variables were included in the analysis. These variables are an MBHC affiliation dummy (MBHC) and an interaction term involving MBHC and the percentage of consolidated MBHC assets accounted for by national bank affiliates (MBHCNBR). If MBHCs tend to operate at least one state-chartered affiliate, MBHC national bank affiliates might be more likely to flip charters. A positive relationship might also reflect charter flips motivated by a desire to reduce the number of different federal supervisors with which a lead MBHC bank must deal.[21] The interaction term is included because MBHCs typically do not radically change their revealed charter preference. National lead MBHC banks are probably less likely to flip charters, the greater the percentage of the company's consolidated assets held by national bank affiliates. So the expected coefficient on the interaction term is negative.

The final bank-specific variable (HERFDEPDIV) used is an indicator of the extent to which an institution is diversified geographically across local markets. It is defined as the sum of the squared deposit shares for each sample bank across all of the local markets in which it operates offices. The shares are calculated using Summary of Deposit data. Higher values indicate less diversification across markets, with the variable taking on its maximum value of 1 for banks that draw all of their deposits from a single market. The expected sign of this variable is unclear a priori. Viewing this variable as another risk proxy, and assuming that risk and the likelihood of a flip tend to be positively related, the coefficient sign should be positive. But this variable might also

[21] The Federal Reserve supervises every MBHC. As a result, changing all affiliate banks to state members could reduce the number of federal supervisors with which the company has to deal.

proxy size (smaller banks tend to be geographically undiversified), which has an indeterminate effect on the probability of a charter flip.

The second group of explanatory variables consists of supervisory assessments of the condition of the bank. The measures used include exam ratings and indicators of the existence of formal and informal enforcement actions. Actually two exam rating indicators are employed: the overall composite rating (CAMEL) and the management rating component (M).[22] These variables change intermittently for the sample banks over time as supervisors conduct exams or impose and remove enforcement actions.[23]

These variables provide insight on the influence of supervisory risk assessments on the propensity of national banks to flip their charter. For example, this could occur if the likelihood of a flip is related to bank risk, and CAMEL ratings contain private information on risk not revealed by standard performance ratios. A related point is that banks may be precluded from converting if their CAMEL rating falls into the "problem bank" range. Using CAMEL scores and enforcement action as explanatory variables may help reveal whether supervisors pressure banks to flip, or flips are motivated at least in part because banks are dissatisfied with past supervisory treatment. These arguments suggest that highly rated and low rated banks are less likely to flip than other banks, ceteris paribus. This implies a quadratic relationship between the probability of a flip and the exam rating, with a positive sign on CAMEL and a negative sign on CAMEL squared (CAMELSQ).

The effect of the management rating is also investigated, because supervisory evaluations of management quality could incorporate nonpublic information. In addition,

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[22] These ratings both take on integer values ranging from 1 (best) to 5 (worst).

the M rating may be the most subjective CAMEL component, implying a greater potential for bank-supervisor disagreement about such scores. Less favorable management ratings seem likely to increase the likelihood of a charter flip. Several different variables are used to capture possible effects of lower management ratings. One is a dummy variable (MFAIR), which takes on a value of 1 for banks with M ratings of 3, 4, or 5. Another dummy variable (MLTCAM) is used to see if the effects of the M rating vary with the bank's composite CAMEL score. This variable takes on a value of 1 for banks whose M rating is worse than their overall CAMEL composite.

The two enforcement action variables (FORMEA, IFORMEA) are dummy variables, taking on values of 1 for banks subject to formal and informal enforcement actions, respectively. Otherwise the variables take on values of zero. Like CAMEL ratings, enforcement actions generally reflect a somewhat subjective supervisory assessment of bank risk and so should be related to the likelihood of a charter flip in a similar way. One key difference, though, is that formal enforcement actions have been publicly disclosed over the sample period. Their public nature may make banks particularly sensitive to the imposition of formal actions, increasing the odds that such actions engender disagreements and promote flips. This also implies that they may be an effective way for supervisors to push problematic banks to flip.

The third group of variables is comprised of indicators of the operating environment of banks. The variables used capture differences in local market competitive conditions and proxy the extent of any advantage linked to having a particular state's charter. Some of these variables (e.g., the measure of de novo entry) are

[23] In addition, the effects of CRA ratings and CAMEL and CRA ratings downgrades were also explored. These specifications resulted in insignificant coefficient estimates.

based on call report information and are updated quarterly. Others (e.g., indicators of market competition) derived from annual Summary of Deposit Data can be calculated only at the end of the second quarter of each year. These June 30 values then remain constant for the sample banks for the three subsequent quarters.

A number of different indicators of local market conditions were used including a herfindahl index of market concentration (HERF), the number of de novo bank entrants over the three-year period lagged three years (NDENOVOT-3), the log of total bank market deposits (LMKTDEP), the percentage of market deposits controlled by out-of-state holding companies (OSHCDR), and market population per bank office (POPOFF).[24] In addition, dummy variables for MSAs or urban markets (MSADUM) and interstate MSAs (INTMSADUM) were also employed. If banks flip charters primarily to gain a performance advantage, they should be more likely to flip if they operate in more competitive or less economically attractive markets. This means that the anticipated signs of the first five variables mentioned previously are negative, positive, negative, positive, and negative, respectively. The coefficients on the dummy variables are ambiguous a priori, since MSA markets tend to be both more competitive and economically attractive than rural markets.

The final variable in this third group is designed to capture the extent of any charter-related performance disadvantage existing in the state in which each national bank has its home office. Rather than using 49 state dummies, the lagged flip out rate for national banks in each state is employed. Specifically, this variable is defined as the cumulative total of national banks that flipped to a state charter in each state over the

[24] All of the market-specific variables refer to the local market from which each sample bank draws the greatest percentage of its total deposits.

previous two-year period divided by the total number of national banks in operation at the outset of the period (PREVFLIPR).[25] This variable is recalculated each quarter over the sample period. The logic behind the use of this variable is that the rate of national bank charter flips is likely to be higher in states in which the state charter provides greater perceived performance benefits. In addition, national banks in these states may ultimately face stronger competition from state peers and so be under more pressure to flip themselves. Thus, the expected sign of this variable is positive. This sort of variable should be a more accurate indicator of changing charter-related disadvantages over the sample period than simple state dummies.

V. Estimation Results

Table 2 contains a small number of alternative "final" versions of the estimated flip equation. The specifications reported reflect the variables found to be the most important and consistent determinants of the probability of charter flips by national banks based on the results of the estimation of various preliminary versions of the flip equation.[26] The estimation results in table 2 only use data for the first 24 of the 32 quarters of the sample period. Holding out the last eight quarters of data permit the out-of-sample forecasting performance of the model to be examined. Omitting the last eight quarters of data does not have large effects on the reported estimation results. In general,

[25] So for example, in the first time period, the numerator of this variable is the number of national banks that converted to a state charter in a sample bank's home office state from January 1, 1992 through December 31, 1993, divided by the number of national banks existing in that state on December 31, 1991.
[26] Basically, the initial stage of the process involved first estimating logit models with only a constant and single explanatory variable on the right-hand side. Variables found to be significant in the first stage were included together in the second stage of equation estimation. The final versions reported in table 2 are third stage equations in which variables found to be insignificant in the second stage were dropped.

the overall explanatory power of the estimated equations is good, and the results are relatively robust across the different specifications.

The first equation in table 2 illustrates the estimation results for the core set of non-supervisory variables found to be significant predictors of the likelihood of a national bank charter flip. In general, and somewhat surprisingly, relatively few significant bank characteristic and environmental variables were found. But the signs and significance of the estimated coefficients on these variables did not change appreciably when the specification of the equation was changed.

The coefficient on the gross loan yield variable was positive and significant in equation 1. This result does not support the notion that national banks flip to boost loan returns presently constrained by stricter legal lending limits. The positive sign could indicate that higher risk banks are more likely to flip. This interpretation is reinforced by the positive significant coefficients on several other variables that also could be viewed as indicative of higher bank risk. These variables are the interest rate risk variable (SGT5R), the home equity-second mortgage variable (HE2MLR), and the insider loan variable (INSDLR).

However, the negative significant coefficient on the 30-89 day nonperforming loan variable (NP89LR) appears to be at odds with this interpretation. Higher levels of NP89LR, presumably indicative of higher credit risk, are associated with a lower probability of a charter flip. This apparent contradiction may reflect closer supervisory scrutiny of this important, more easily quantifiable measure of risk in evaluating banks that wish to change charters. It also might indicate that the management of banks experiencing credit quality problems focuses their attention on this issue deferring longer-term strategic decisions such as changing their charter. The more comprehensive NPLR variable was also found to have a significant negative effect on the probability of a charter flip, but was not as powerful. This finding, in conjunction with an insignificant coefficient on NCLR when it was tried, suggests that NP89LR is driving the NPLR result.

The coefficients on the MBHC dummy and the associated interaction term are both significant with reasonable signs. The positive coefficient on the former implies that MBHC affiliates are more likely to flip, but this likelihood falls as the percentage of the MBHC's consolidated assets in national banks increases.

The geographic diversification variable was also significant, but with an unanticipated negative sign. This result indicates that the less geographically diversified the bank, the less likely it is to flip its charter. Again, this result might be capturing a size effect.

Three environmental variables appear in equation 1 with significant coefficients. In all three cases, the signs are plausible. Higher values of the first two variables, the percentage of market deposits controlled by out-of-state holding companies (OSHCDR), and the lagged number of de novo entrants (NDENOVOT-3), imply more competitive markets. So the positive coefficients on these variables suggest that national banks are likely to flip in more competitive markets.

The last environmental variable, the percentage of home state national banks that flipped over the previous two years (PREVFLIPR), is the proxy for any sort of state charter-related competitive advantage. The significant positive coefficient suggests that national banks are more likely to flip in states where flip activity has been greater in the past, presumably as a result of a more favorable environment for state banks. The higher propensity to flip might also reflect greater competitive pressure coming from advantaged state peers.

The last two variables in equation 1 reflect the assumed form of the baseline hazard function. Based on a comparison of the preliminary results obtained when a number of relatively simple functions of event time were examined and informed by the non-parametric hazard estimates shown in Figure 1, a quadratic specification was adopted. The estimated coefficients on the time terms are both significant and indicate that the baseline hazard initially falls and then rises with time.

The results for the nontime variables are not sensitive to the choice of a quadratic baseline function. In fact, if all of the equations in table 2 are re-estimated as Cox models, where the baseline hazard function is not explicitly specified, the coefficient estimates and significance levels of all of the independent variables are basically unchanged.[27]

Two other non-supervisory variables were found to be statistically significant in some cases. The results of including these variables are illustrated in equations 2 – 4 in table 2. Equation 2 adds COMLR, the ratio of commercial loans to total assets, to the core set of independent variables appearing in equation 1. The coefficient is positive and marginally significant, indicating greater bank involvement in commercial lending increases the likelihood of a charter flip. This result might reflect either the effects of potentially binding lower legal lending limits on national banks or merely be another manifestation of a positive risk-flip relationship found for a number of other independent

[27] This statement holds for alternative methods of dealing with tied failure times and if robust variance estimators are employed.

variables. Equation 3 shows the results of using a non-continuous transformation of the commercial lending variable in place of COMLR. This variable, COMLD75 is a dummy variable taking on a value of 1 for banks with COMLR values in the top quartile, otherwise set equal to 0. This transformation was investigated because the effect of COMLR on the likelihood of a charter flip might be non-linear. The estimated coefficient on this variable is again positive, but the z-value is considerably higher supporting the use of this specification.

Equation 4 adds NONIER, the ratio of noninterest expenses to net revenue, to the set of independent variables appearing in equation 1. The estimated coefficient is positive and marginally significant, suggesting that banks with higher expenses are more likely to flip their charter, presumably to lower their costs. Neither this variable, nor a transformation similar to the one used for COMLR, appear in any of the other equations in table 2, because the expense ratio measures were never significant when supervisory variables are added to the specification.

Before proceeding to a discussion of the effects of including the supervisory variables in the flip equation, the potential explanatory variables found to be insignificant should be detailed. This list of variables include measures of bank size (LASSET), capitalization (EAAR, NCAPR), risk (LAR, NCLR), loan portfolio composition (WSLAR, CRLR), interest rate risk (LGT5R, TAGT5R), profitability (PTROA, PTROE), nontraditional activities (RNONIIR), and the number of recent mergers in which a bank was involved (NM4Q). Several environmental variables also were never found to be significant (HERF, LMKTDEP, POPOFF, MSADUM and INTMSADUM).

The remaining equations in table 2 show the results of adding supervisory variables to the basic specification of equation 1 or equation 3. In equation 5, the estimated coefficients are significant on the two CAMEL composite terms (CAMEL and CAMELSQ). The sequence of positive and negative signs indicates that the probability of a charter flip first rises and then falls with a bank's composite exam score.[28] The formal enforcement action dummy was also found to be significant with a positive coefficient. National banks subject to formal enforcement actions are more likely to flip their charter. Equation 6 adds the commercial lending dummy to the set of independent variables appearing in equation 5. Again the estimated coefficient on the commercial lending dummy is positive but only marginally significant. Equations 7 through 10 show the effects of adding the two management rating dummies to equations 5 or 6. In all cases, the estimated coefficients on the management rating variables are positive and significant; generally indicating that the likelihood of a charter flip increases the worse a bank's management rating. Also the addition of the supervisory variables does not greatly alter the signs or significance of the non-supervisory variables.

Likelihood ratio tests confirm that the addition of the supervisory variables significantly increases the explanatory power of the model. To illustrate, the basic model described by equation 3 in table 2 is nested within the models given by equations 6, 8, and 10, which add 3 or 4 supervisory variables to the basic specification. In the case of nested models, the relevant test statistic is distributed as a chi-square with k degrees of

[28] Equation 5 was also re-estimated after dropping all banks rated 4 or 5. The rationale is that problem banks are precluded from flipping and so should be treated as censored instead. Dropping these observations did not alter the estimation results in any significant way, including the signs and statistical significance of CAMEL and CAMELSQ.

freedom, where k is the number of additional variables appearing in the unrestricted model. Formally,

$$(2) \quad LR = -2(\ln L_r - \ln L_u)$$

where:

LR = the likelihood ratio statistic

L_r = the log likelihood of the restricted model

L_u = the log likelihood of the unrestricted model.

The relevant chi-square value when equation 3 is compared to equation 6 is 22.18, well above the critical value.[29] Similar results are evident when equation 3 is compared to equations 8 and 10.[30]

Taken as a whole, these results suggest that banks judged to be somewhat more risky by supervisors are more likely to flip their charter. But precisely how to interpret these results are unclear, since supervisory ratings are inherently subjective. These results could be consistent with the notion that banks with higher risk – higher return strategies tend to switch to more compatible supervisors. They could also be viewed as support for the notion that supervisors push correctly identified higher risk banks to flip. They might also reflect bank dissatisfaction with their existing supervisory treatment or bank scapegoating of supervisors in the wake of disappointing performance. It might be possible to obtain some clarifying insight on what is occurring by incorporating expected ratings into the analysis.[31] This is a subject for future research.

[29] The critical (α=.10) chi-square values are 6.25 and 7.78 for 3 and 4 degrees of freedom, respectively.
[30] Equation 3 vs. 8 yields a chi-square value of 30.96. Equation 3 vs. 10 results in a chi-square value of 27.33.
[31] For example, a measure of the extent of possible supervisory misclassification could be obtained by comparing a bank's actual rating to a predicted rating.

VI. The Forecasting Accuracy of the Model

Only a casual analysis of the forecasting accuracy of the estimated model is attempted here. Given the relatively small number of banks that flipped over the time period, the conventional approach of using the estimated model to predict the flip probabilities for a holdout sample is not employed. Instead the set of independent variables labeled equation 10 in table 2 is used to produce two different forecasts of the number of bank flips. The two different forecasts reflect two potential alternative uses of this sort of model. One use would be to produce forecasts of the total number of flips in future time periods. The other use would be to predict the likelihood of specific banks flipping. In both cases, the forecasts are produced with the model specification held constant, but with the model coefficients updated each quarter from 2000:Q1 through 2001:Q4.

The model is first used to generate the expected number of flips in each time period. This forecast is obtained by summing the predicted flip probabilities for all banks in the sample at each value of time. The expected number of flips each period is plotted vs. the number of actual flips in Figure 2. In general, the model forecasts track the number of flips relatively closely.

Equation 10 is also used to examine the ability of the model to correctly identify flipping and non-flipping banks out-of-sample. This exercise classifies banks as flipping or non-flipping in each quarter from 2000:Q1 through 2001:Q4. Banks were predicted to flip in each forecast quarter if their estimated conditional flip probability was in the top three deciles at that time. The results of this exercise are summarized in table 3. Panel A of table 3 shows for each forecast quarter the number of banks predicted to flip vs. their actual flip status. Panel B of table 3 uses the data in panel A to show how well the model identifies flipping banks at various lead times relative to the quarter in which they ultimately flip.

Examination of the results in table 3 generally reveals that the model does a decent job of predicting charter flips. For example, panel B shows that the model correctly identifies 64.5 percent of banks that flip in the current quarter. Interestingly, the model correctly identifies 70.4 percent of banks that ultimately flipped two quarters prior to their flip quarter. The percentages correctly identified at the other forecast horizons examined are in the low 60's. These percentages imply Type I error rates of 30-40 percent. The last line of panel A implies Type II error rates of roughly 30 percent.

Several strategies might be used to improve the forecasting performance of the model. Greater predictive power might be obtained if possible noise in the bank financial characteristic variables, stemming from the use of end-of-quarter data, was reduced. This might be accomplished if such variables were defined as four-quarter averages. The slightly better accuracy of the model in predicting flips two quarters ahead suggests that better performance might also be obtained if a longer lag is used between the time at which the explanatory variables are measured and flips occur. Here the flips that occur in the current quarter are generally related to explanatory variables measured at the end of the previous quarter. This lag could be lengthened by some small number of quarters to reflect the realistic possibility that the decision to flip predates the actual occurrence of the flip and could reflect circumstances and conditions prevailing earlier that might no longer be readily apparent. More detailed investigation of the appropriate lag is a subject for future research.

VII. Summary and Conclusions

In this paper, a discrete-time logistic hazard model is used to identify the factors that influenced the probability of charter flips by national banks over the 1994 – 2001 time period. Relatively few bank financial variables were found to be significant explanatory variables. The estimated coefficients of a number of these variables (the gross loan yield, the longterm securities ratio, the insider loan ratio, and possibly the commercial lending dummy) suggest a positive relationship between risk and the likelihood of a charter flip. The positive coefficient on the home equity-second mortgage loan variable might also be interpreted in this fashion if serves as a proxy for higher risk, sub-prime lending. The positive coefficient on the commercial lending dummy might also indicate that national banks more heavily involved in this activity might flip to obtain higher legal lending limits associated with some state charters.

The exceptions are the negative significant coefficients on the nonperforming loan ratio and geographic diversification variable. The former result might indicate that the loan quality ratio is viewed as a more contemporaneous, clearer signal of the magnitude of a bank's credit risk than these other measures, and as such might raise supervisory concerns about the motives for or potential costs of a bank flip.

The estimation results also reveal that MBHC lead banks are more likely to flip, ceteris paribus, but this propensity decreases the higher the percentage of consolidated holding company assets in national bank subsidiaries.

Several environmental variables had significant coefficients in the charter flip model. The results reveal that the greater de novo entry has been in the recent past, the greater the likelihood of a charter flip. A similar effect was found for the percentage of market deposits controlled by out-of-state bank holding companies. Since both of these variables can be interpreted as indicators of greater market competition, these findings suggest flips are more likely in more competitive markets.

The lagged national bank flip rate was also found to be significantly and positively related to the likelihood of a charter flip. This finding presumably reflects the existence of, and competitive pressures attributable to, advantages associated with state charters.

Supervisory variables also are significantly related to the likelihood of charter flips, even after including the effects of the set of variables previously discussed. Empirical support was found for a quadratic relationship between composite CAMEL ratings and the likelihood of a charter flip. Formal enforcement actions also increased the likelihood of a flip. Finally, the management rating dummies indicate that less favorable M ratings also increase flip likelihoods. As noted previously, there are a considerable number of possible explanations for this pattern of results. It could imply that flips are motivated by a desire of bank management to find a more amenable supervisor. Or it might reflect supervisory pressure on higher risk banks to flip. Further research is required to identify which of the potential explanations are more likely.

The limited examination of the forecasting accuracy of the model revealed modest success in identifying converting banks. There are a number of reasons why this might be the case, including the use of quarterly data and the short lag between the time at which the data are measured and flips occur. A more rigorous, complete analysis of these issues will be the subject of future research.

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Table 1

Number of Sample National Banks Converting to State Charters

1994:Q1 - 2000:Q4

Quarter	Number of Flips	Quarter	Number of Flips
1994:Q1	5	1998:Q1	3
1994:Q2	14	1998:Q2	0
1994:Q3	4	1998:Q3	3
1994:Q4	5	1998:Q4	3
1995:Q1	3	1999:Q1	5
1995:Q2	8	1999:Q2	0
1995:Q3	2	1999:Q3	4
1995:Q4	2	1999:Q4	3
1996:Q1	0	2000:Q1	2
1996:Q2	2	2000:Q2	2
1996:Q3	0	2000:Q3	5
1996:Q4	3	2000:Q4	2
1997:Q1	1	2001:Q1	4
1997:Q2	3	2001:Q2	8
1997:Q3	2	2001:Q3	3
1997:Q4	4	2001:Q4	5

Figure 1: Life Table Flip Hazard Estimates

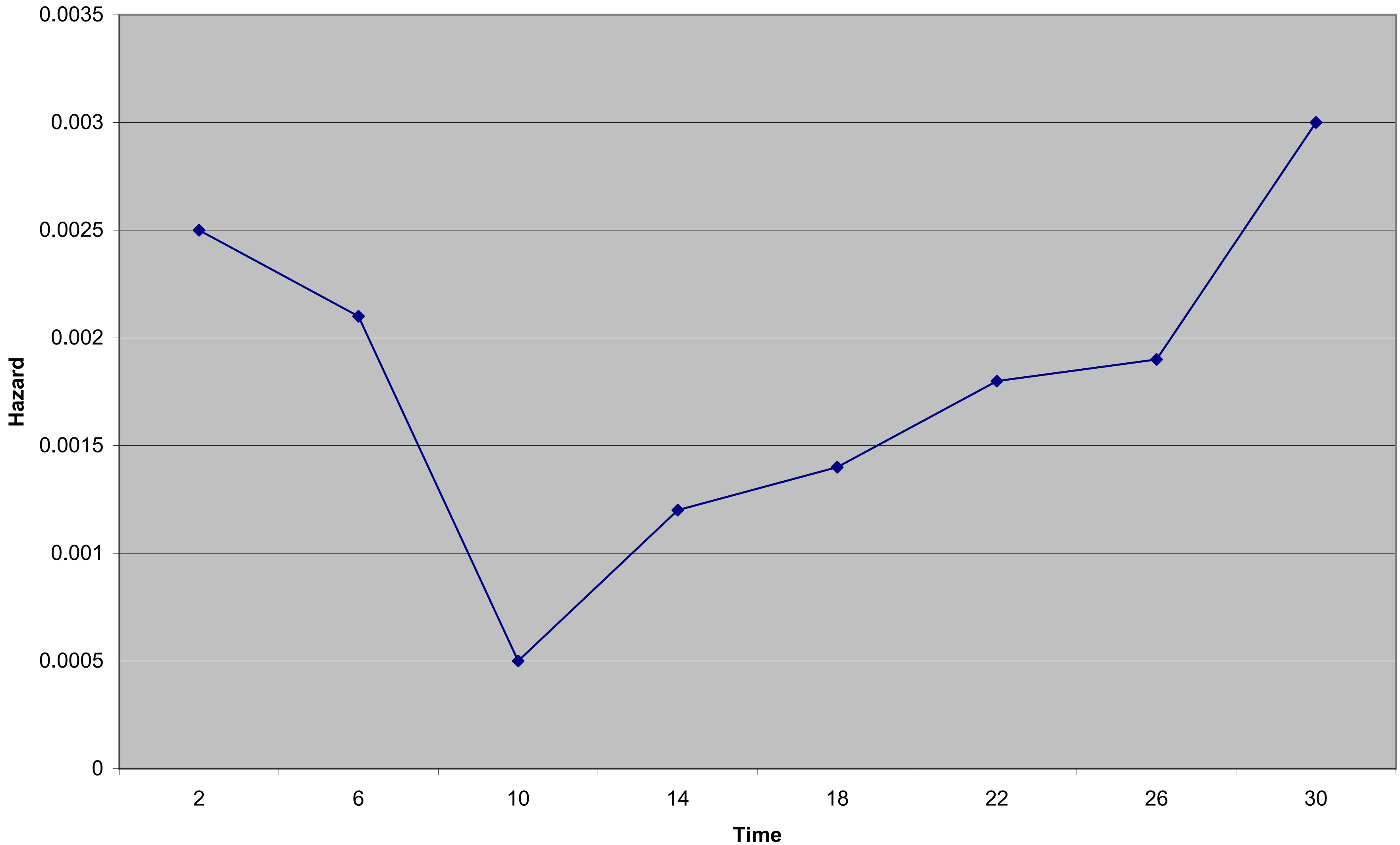

Table 2

Discrete Logistic Hazard Equations

Estimation Period: 1994:Q1 - 1999:Q4

Equation

	(1)		(2)		(3)		(4)		(5)		(6)		(7)		(8)		(9)		(10)	
Variables	Coefficient	Z-Stat	Coefficient	Z-Stat	Coefficient	Z-Stat	Coefficient	Z-Stat	Coefficient	Z-Stat	Coefficient	Z-Stat	Coefficient	Z-Stat	Coefficient	Z-Stat	Coefficient	Z-Stat	Coefficient	Z-Stat
CAMEL									3.262696	3.54	3.18261	3.46	3.745182	3.77	3.651078	3.68	3.62248	3.84	3.53486	3.76
CAMELSQ									-0.72052	-3.09	-0.70966	-3.06	-0.927716	-3.55	-0.91353	-3.51	-0.779854	-3.30	-0.76685	-3.27
FORMEA									1.084044	2.79	1.0671	2.76	0.967594	2.49	0.956065	2.46	1.03758	2.69	1.0183	2.65
MFAIR													1.01785	3.17	1.024079	3.19				
MLTCAM																	0.70695	2.38	0.71535	2.41
HERFDEPDIV	-1.114945	-2.09	-1.06881	-2.00	-1.068728	-2.00	-1.12353	-2.10	-0.981349	-1.84	-0.94952	-1.78	-1.01148	-1.89	-0.985312	-1.84	-1.03779	-1.94	-1.01079	-1.89
GLYLD	23.53379	2.00	22.20770	1.88	22.56081	1.91	22.69474	1.94	22.43441	1.89	21.8785	1.84	21.56381	1.83	20.61192	1.74	21.85173	1.84	21.07167	1.77
NP89LR	-45.05194	-2.23	-45.79107	-2.28	-46.92756	-2.33	-46.62636	-2.33	-56.01364	-2.70	-56.67656	-2.75	-59.48255	-2.85	-60.28091	-2.90	-58.11629	-2.79	-58.90434	-2.84
SGT5R	2.171738	1.70	2.44817	1.89	2.45903	1.91	2.37894	1.85	2.40941	1.87	2.63931	2.04	2.26052	1.76	2.49032	1.93	2.2933	1.78	2.52168	1.95
HE2MLR	8.429122	2.39	8.15723	2.30	8.10302	2.27	8.03047	2.27	7.24476	2.03	7.03214	1.95	6.9752	1.97	6.72278	1.87	7.09773	2.00	6.86804	1.91
INSDLR	16.99049	2.46	14.95003	2.14	14.46966	2.07	17.19262	2.50	18.11631	2.61	16.01501	2.28	19.20021	2.77	16.96646	2.40	19.13132	2.76	16.95687	2.40
COMLR			2.49051	1.69																
COMLD75					0.524489	2.17					0.41162	1.68			0.42173	1.72			0.42044	1.71
NONIER							1.39548	1.77												
OSHCDR	0.997349	2.31	0.91621	2.12	0.90023	2.08	0.94917	2.22	0.95296	2.21	0.87955	2.03	0.97357	2.27	0.89819	2.09	0.978341	2.28	0.90116	2.09
NDENOVOT-3	0.062561	2.95	0.05803	2.66	0.058313	2.70	0.06115	2.84	0.06114	2.81	0.056954	2.57	0.062301	2.85	0.058322	2.63	0.062825	2.88	0.05882	2.65
PREVFLIPR	8.640777	3.67	8.49765	3.58	8.53137	3.60	8.80631	3.71	8.75625	3.70	8.57538	3.61	8.63931	3.63	8.44364	3.52	8.79932	3.70	8.61272	3.60
MBHC	2.455701	2.19	2.40145	2.17	2.46098	2.21	2.58909	2.31	2.67702	2.45	2.65881	2.44	2.70539	2.46	2.69493	2.46	2.7228	2.48	2.71411	2.49
MBHCNBR	-3.246878	-2.11	-3.25849	-2.14	-3.34737	-2.19	-3.30387	-2.16	-3.40812	-2.27	-3.47738	-2.32	-3.40311	-2.26	-3.47829	-2.32	-3.42812	-2.28	-3.51022	-2.35
TIME	-0.207672	-3.15	-0.21037	-3.18	-0.21045	-3.18	-0.18986	-2.84	-0.17141	-2.54	-0.17718	-2.61	-0.157607	-2.32	-0.16386	-2.41	-0.16001	-2.36	-0.16591	-2.44
TIMESQ	0.00765	2.89	0.00773	2.91	0.00774	2.92	0.00709	2.65	0.00655	2.44	0.00672	2.49	0.00615	2.28	0.00634	2.35	0.00624	2.31	0.00641	2.37
CONSTANT	-7.523291	-6.33	-7.63463	-6.43	-7.54913	-6.37	-8.47696	-6.51	-11.07726	-7.22	-10.98238	-7.18	-11.30901	-7.29	-11.15596	-7.21	-11.61063	-7.46	-11.48434	-7.42
NOBS	46257		46257		46257		46251		46247		46247		46247		46247		46247		46247	
Log Likelihood	-547.286		-545.941		-545.015		-545.781		-535.295		-533.923		-530.971		-529.534		-532.779		-531.352	
Chi-square	70.15		72.84		74.69		73.14		94.1		96.84		102.75		105.62		99.13		101.98	
Pseudo R^2	0.0602		0.0625		0.0641		0.0628		0.0808		0.0831		0.0882		0.0907		0.0851		0.0876	

Figure 2: Model Forecast Accuracy

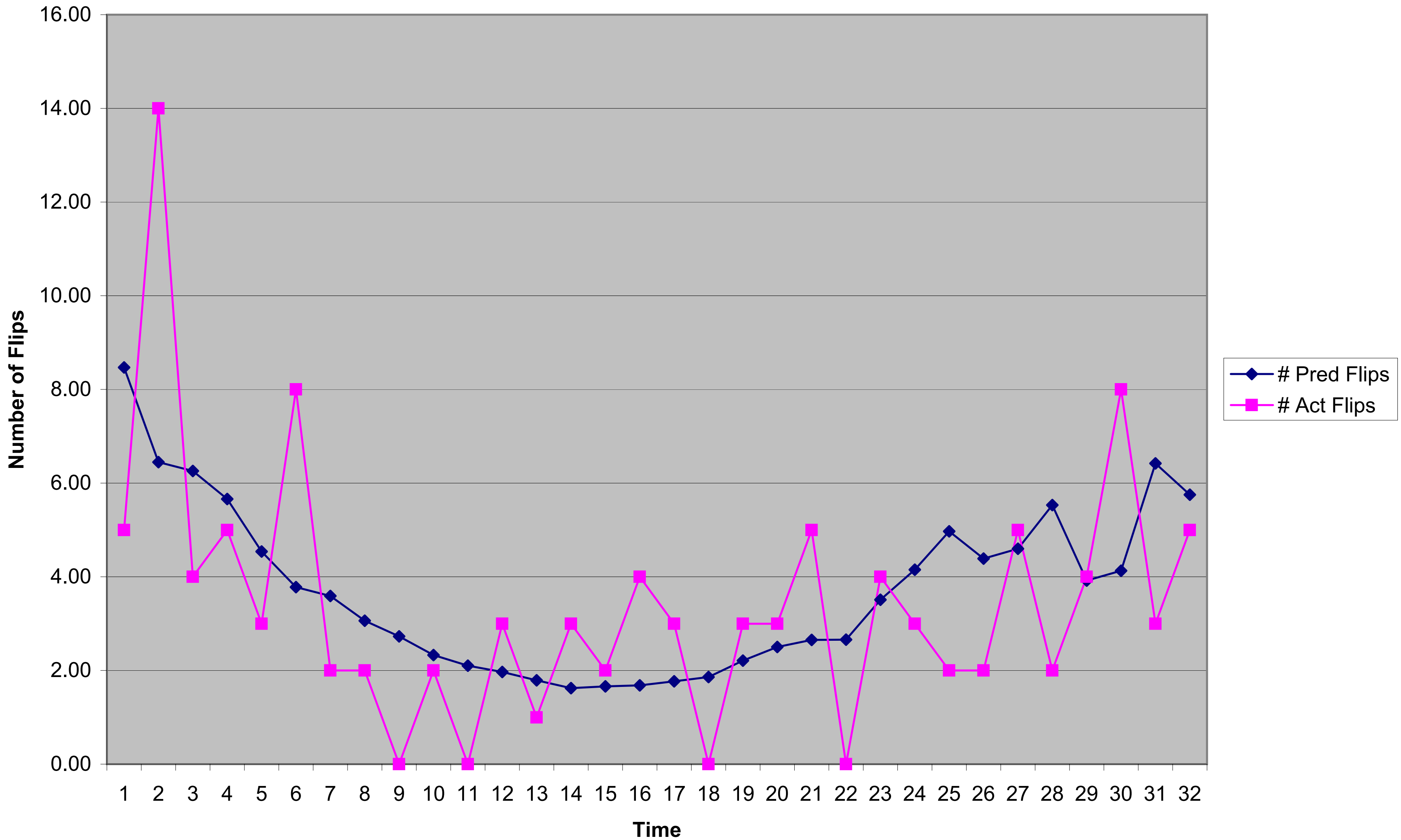

Table 3: Panel A

Out-of-Sample Classification Accuracy

Estimates Based on Equation 10

Classification Cut-Off: Conditional Probability in Top Three Deciles

Forecast Quarter

	2000:Q1		2000:Q2		2000:Q3		2000:Q4		2001:Q1		2001:Q2		2001:Q3		2001:Q4	
Flip Status	# of Banks Predicted to Flip	Total Number	# of Banks Predicted to Flip	Total Number	# of Banks Predicted to Flip	Total Number	# of Banks Predicted to Flip	Total Number	# of Banks Predicted to Flip	Total Number	# of Banks Predicted to Flip	Total Number	# of Banks Predicted to Flip	Total Number	# of Banks Predicted to Flip	Total Number
Flipped 2000:Q1	2	2														
Flipped 2000:Q2	1	2	2	2												
Flipped 2000:Q3	2	5	3	5	1	5										
Flipped 2000:Q4	2	2	2	2	2	2	2	2								
Flipped 2001:Q1	2	4	2	4	2	4	2	4	2	4						
Flipped 2001:Q2	3	8	5	8	6	8	7	8	5	8	6	8				
Flipped 2001:Q3	3	3	3	3	3	3	2	3	3	3	3	3	2	3		
Flipped 2001:Q4	1	5	0	5	2	5	2	5	2	5	3	5	2	5	3	5
Non-Flips	453	1535	447	1519	441	1498	436	1480	434	1469	428	1448	429	1434	426	1427

Table 3: Panel B

Out-of-Sample Classification Accuracy

Model Identification of Converting Banks at Alternative Forecast Horizons

Estimates Based on Equation 10

Classification Cut-Off: Conditional Probability in Top Three Deciles

Flip Time Relative to Forecast Quarter	# of Predicted Flips	# Actual Flips	Predicted/Actual
Same Quarter	20	31	0.645
One Quarter	18	29	0.621
Two Quarters	19	27	0.704
Three Quarters	14	22	0.636
Four Quarters	12	20	0.600