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Abstract: The amount of risk that banks assume in lending is a key consideration in the amount of lending that banks ultimately will do. The relationship between default risk and lending levels is addressed here by deriving risk measures based on local economic industry mixes and locational characteristics of bank groups and then testing the degree to which differences in risk in local lending markets affect the asset allocation decisions of banks. FDIC call report data for West Virginia banks are combined with quarterly sectoral failure rate data and earnings data by sectors for the analysis.

Holding company risk measures reveal potential trouble with using simplified measures such as dummy variables indicating inclusion in multi-bank holding companies, since the risk effects of holding company inclusion vary according to particular situations. The risk measures also clearly illustrate substantial intrastate variation in risk among different banks in different county lending environments. Given the derived risk variables, ordinary least squares regression is used to estimate the effect of the risk variables and other independent variables on bank lending amounts. Regressions are estimated both for total lending and for commercial lending. The results are encouraging given their findings of an important negative risk effect, along with the expected size effect.

Estimating Bank Lending Risk and its Effect on Asset Allocation

Introduction

The amount of risk that banks assume in lending is a key consideration in both the amount of lending that banks ultimately will do and in the proper assessment of their possibility of failure. Each of these concerns has in turn driven legislation and policy concerning bank lending and risk. The amount of lending that banks do can have an important, possibly detrimental, influence on local economic development. Given this link, some banks are thought to be lending too little, and one aspect of community reinvestment legislation and associated activism is to encourage greater amounts of lending by local institutions. Banks have competing obligations, however, which compel them to look carefully at the riskiness of composing portfolios of particular assets. Regulators who insure the deposits of commercial banks are also concerned with the riskiness of bank portfolios, especially as they may exceed reasonable risk standards and jeopardize the deposits of the bank.

This research addresses both questions by deriving risk measures based on local economic industry mixes and tests the degree to which differences in risk in local lending markets affect the asset allocation decisions of banks. As such it will provide a step beyond current efforts which, while properly concerned with geographical diversification opportunities, lack both a sufficient theoretical perspective and, more seriously, often provide only a very crude approximation of existing diversification opportunities. The results of the study here should also help assess the relative importance of factors which are thought to influence bank asset allocation. By better controlling for the risk effects engendered by differences in local economic conditions, findings about the remaining influence of such things as group bank membership and size/economies of scale should become more clear. In addition, the results of more refined analysis of lending risk should be useful in evaluating suggestions to possibly adjust deposit insurance premia to reflect state-level risk (Cebula et al, 1993) or to reflect bankruptcy risks of portfolios as calculated using national models (Chirinko and Guill, 1991).

Prior to the risk measure derivation and empirical testing, existing literature related to diversification and failure is examined, revealing a number of interesting approaches to assessing bank risk. This is followed by a brief theoretical discussion of a bank asset allocation model which incorporates risk aversion, imperfect markets, and group banking. The implications of the theoretical model for empirical testing are also discussed.

The empirical work builds from the theoretical model by testing the influence of differences in local economic structure, as they influence expected business failure rates and their variances, on bank asset allocation. Initial empirical work produces estimates which summarize business failure rate and variance measures for banks in the sample. A time series approach using failure rate data as a proxy for loan losses is used to calculate the risk estimates. In addition, differences among local markets and among group banks with different configurations will be explored to illustrate the importance of accounting for actual default risk environments of different banks.

Given the derived risk variables, ordinary least squares regression is used to estimate the effect of the risk variables and other independent variables on bank lending amounts. Regressions are estimated both for total lending and for commercial lending. Other independent variables will be drawn largely from the theoretical model, with some additional variables included for comparability to existing models. The additional variables include total assets, market share, market size and income growth, group bank total assets, and measures to indicate loan demand from local, rather than national, lending resources.

Literature Review

Diversification

Literature focussed on geographical diversification of group bank systems consists of surprisingly little research, considering the importance of bank organizations being spatially diversified or functioning in diversified economic environments in order to sustain higher levels of commercial lending without undue risk. Most of the mention of this consideration is only in passing, with very little consideration given to the actual question of diversification.

Several researchers have discussed potential diversification benefits without explicitly modelling differences in overall group banking diversification. Snodgrass (1971), for example, notes reduction simply through multi-locational operations as it reduces exposure to disastrous risk and points out that even greater diversification can be achieved with different rural market combinations and urban-rural combinations. Rose (1987) hints at a more formal approach by noting that "if true diversification is achieved (such that economic conditions are not positively correlated in the set of local markets entered by a branching organization), then a downturn in deposit flows, loan demand, or loan repayments in one market will be offset by an increase in deposit flows, loan demand, or loan repayments in another market" (p. 223). Each of these studies not only discussed diversification, but also noted important qualifiers, pointing out that operation in more than one market is not sufficient to achieve a large degree of diversification.

Some evidence has been presented concerning the effects of diversification on deposit variation and on lending behavior. Wacht's (1968) theoretical analysis and Lauch and Murphy's (1970) empirical application both verify that branch systems can lower deposit variability. Although contradictory evidence was presented by Anderson, Haslem, and Leonard (1976), Rose (1987) notes that the more persuasive case is made for a reduction in liquidity risk in group banking systems.

Other work has examined the implications of diversification on loan portfolio risk. Cherin and Melicher (1987) use the measure "number of markets served" constructed from FDIC branching data to serve as a measure of diversification and analyze the mean and standard deviation of return from the loan portfolio of bank groups. They find that "branch banking, even when confined to state boundaries, seems to offer both absolute and relative risk reduction in bank loan portfolios". Corgel and Gay (1987) examines monthly sectoral employment changes in U.S. metropolitan areas to assess the benefits to mortgage lenders of diversifying across MSAs, using a formal portfolio approach to illustrate the potential advantages of geographic diversification. An analysis of correlations among the first principal components from different MSAs revealed only moderate positive correlation, indicating some possible benefits to diversification. Ogden, Rangan, and Stanley (1989) conduct a similarly broad analysis of diversification benefits for mortgage portfolios based on reported foreclosure rates in the twelve Federal Home Loan Board districts for 1974-1985. Constructing portfolios for each Federal Reserve district varying from zero diversification, i.e., portfolio composed entirely from within the district, to 100% diversification, their analysis reveals that even small levels of diversification led to substantial declines in portfolio risk for all districts.

Liang and Rhoades (1988) are concerned specifically with the effect of geographic diversification on risk in banking, defined as the probability of bank failure and captured by a variety of risk measures. Geographic diversification is measured as the inverse of the squared percentages of total deposits in the different markets, specified as MSAs (or NECMAs) or counties in non-metropolitan areas, in which a bank operated. Liang and Rhoades estimated their models using data from the FDIC year-end call reports from 1976-1985 for 5,509 banking organizations. In all but one definition of the dependent risk variable, diversification is found to have a negative and statistically significant effect on the level of risk in a banking organization. The elasticities, measured at the means, were quite low, however.

Liang (1989) examines the structure-conduct-performance relationship between profits, variation in profits and market concentration with the inclusion of local market uncertainty considerations. The main hypothesis is that previous efforts to calculate the effect of market concentration on firm profitability may be erroneously attributing effects to market concentration which may be due to uncertainty, since concentrated markets are more likely to be those with greater uncertainty. The uncertainty may come from the deposit or loan side and can be attributed to lower levels of diversification in smaller local economies.

Liang's specification proceeds from the structural model specified by Clark (1986), from which follows a two-equation system with profits and risk (standard deviation of profits) as dependent variables. The risk equation specification includes several calculated variables of significant interest. The standard deviation of per capita income was included as a general measure of market uncertainty, and the standard deviation of market deposits was used to indicate deposit market uncertainty. Liang also fits simple regressions of both bank deposits and bank loans as functions of market income and used ($1-R^2$) to indicate the uncertainty in deposit supply and loan demand. The residuals were also used to calculate a covariance term for use in the risk equation.

Hawawini and Suary (1990) examine potential diversification benefits of intrastate and interstate bank mergers by analyzing residual bank stock returns. Intrastate bank comparisons showed significant positive correlations between banks in the same state ranging from 5% to 67%. A remarkable 95% of the money center bank pairs had significant positive correlations in residual returns. Very few significant negative correlations were found. Hawawini and Suary also examine banks within regional groups and found similar results -- only limited diversification benefits appeared to be available within regions. Finally, interstate correlations showed that interstate diversification offered little benefit over intrastate mergers for California banks, but that interstate diversification might lead to significant benefits for Texas banks.

Default Risk, Business Failure, and Bank Failure

Since diversification effects on bank asset allocation can be considered to be largely driven by default risk considerations, which derive from business failures and influence bank failure, these topics are also of concern in examining diversification. This section will summarize several articles which analyze one or more of these topics and contribute to understanding empirical realities related to default risk.

Chirinko and Guill (1991 and 1992) are concerned with the proper setting of risk-based deposit insurance and capital standards based on evaluations of the riskiness of bank portfolios. While the approach focusses on macroeconomic influences, the methodology and the assessment of credit risk are important developments relevant to local bank portfolios and the localized influences on them. Specifically, the credit risk assessment is portfolio-theory based, where the risk of depository institutions is determined by loan holdings by sector and where the portfolio can be characterized by a "loan loss distribution reflecting industry means, variances, and covariances" (p. 786).

Chirinko and Guill proceed in a series of steps designed to link the default rates of particular industries to potential changes in key macroeconomic variables. In particular, Chirinko and Guill use a combination of an econometric model and an input-output model to gauge the effect of different values of exchange rates, the federal deficit, monetary policy, and commodity prices. The resulting distributions of costs, revenues, and federal funds rate are fed into the default rate model to project default rates for different industries resulting from different outcomes of exogenous variables. Given distributions of industry default rates in the various scenarios, an inter-industry variance-covariance matrix is calculated. The particular risk characteristics of bank portfolios depend on the variance-covariance matrix and the particular weighting scheme of the loan portfolio of the individual bank. Based on simulations for five possible portfolios, Chirinko and Guill conclude that it is of great importance to account for the distribution of assets within bank portfolios since "portfolio concentrations and asset covariations ... are of first order importance" (1991, p. 241).

Barth, Belton, and Cebula (1993) also consider bank failures, but focussed upon geographic differentials in bank closing rates. Unlike the explicit industry focus of Chirinko and Guill, Barth et al. seek to explain geographic differentials by investigating regional factors such as concentration of economies in particular industries. They model bank failures as a function of cost of deposits, loan charge-off rates, capitalization, unemployment rates, gross state product growth rate, average percentage of state product deriving from oil and natural gas extraction, and indicators of whether states were unit bank states or allowed unlimited branching. Empirical estimation, based on state closure rates over the 1980-1992 period, indicates that closure rates were higher in areas with higher unemployment and concentration in the volatile energy sector, verifying the importance of these regional factors in bank closure rates.

Cebula, Chou, and Schaffer (1993) also consider geographic differentials in failure rates of financial institutions, but examine savings and loan associations and consider a different set of factors more closely related to questions of risk and return. Cebula et al. model the state S&L failure rate as a function of oil and gas importance, the average remaining balance on mortgage portfolios, and the means and variances of the annual growth rates of state product, the cost of funds, and the effective mortgage rate on conventional loans. Cebula et al. fit a heteroskedastic tobit model to state data from 1979-1988 and find significant effects for several of the independent variables, mostly as expected. Interestingly, the oil and gas extraction variable dominates the general variability of GSP measure, with the GSP variability not found to be statistically significant.

Platt (1989) examines interindustry spillovers in business failure. Platt proposes a simplified model whereby a given industry's failure rate is a function of current and lagged economic conditions, current and lagged financial condition, and current failure rates in other industries. Platt uses quarterly national data on industry failure rates from Dun and Bradstreet for 1950-1981for sixteen industries. Three-stage least squares is employed to correct for simultaneity bias and account for covariation in error terms among sectors. The estimated equations reveal markedly different results for different industries, but do identify statistically significant influences of at least one financial condition, one economic condition, and one other industry on each industry's failure rate. The variation among interindustry effects was also substantial, with mining showing very little sensitivity to other industry failure rates and retail trade appearing the most sensitive to failures in other industries. Both results are consistent with an economic base perspective where basic sectors such as mining driving the demand for non-basic sectors such as retail trade. Overall, thirty of the potential 120 interindustry coefficients were found to be statistically significant. All significant linkages were positive.

Together, existing research concerning diversification, portfolio risk, and bank failure illustrate a clear concern for the measurement of risk and its implications for bank behavior and failure probabilities. It also provides a useful foundation for further examination of risk and diversification in existing markets. The approach used here builds on these efforts by incorporating a number of their concepts in developing measures from state and county level data and fully incorporating the locational structure of bank groups.

Theoretical Perspective

The empirical model investigated here is also motivated by the the theoretical model of asset allocation derived in Sorenson (1995). This theoretical perspective follows from the portfolio view of bank asset allocation developed by Hyman (1972), Hart and Jaffee (1974), and Pyle (1971), the inclusion of imperfect markets as in Klein (1971), Langohr (1982), Hannan (1991), and Jones (1991), and the combination of the two essential elements in Sealey (1980), Zarruk (1989), Mitchell (1983), and Clark (1986).

The Sorenson (1995) model includes imperfect local lending markets, risk aversion of bank decision-makers, cost differentials between banks, and group banking. The model is developed from an oligopolistic equilibrium perspective, assuming Cournot behavior. It examines lending by each bank in a particular market with respect to exogenous parameters including deposit market shares of all banks in the market, expected loan default rates, the variance of loan default rates, lending unit costs for all banks within a given market, a risk aversion parameter, bank capital, and general influences on total market loan demand. The model assumes that bank managers maximize expected utility by selecting quantities of loans and securities subject to a balance sheet constraint, a demand function for loans, an exogenous, market-determined rate for securities, and exogenous deposit market-shares and lending costs. Given the constraints, the model simplifies to a single loan quantity decision.

The model is also explicitly extended to group banking situations to investigate the effects of diversification on bank lending behavior.

A simplified reduced form of the theoretical model can be specified as:

Loan Amount = f(expected default rate, variance of default rate, cost, demand conditions, market structure, capitalization)

The model provides several empirically testable hypotheses concerning these exogenous influences. The most central to this research is that bank lending is negatively related to the expected default rate and variance of the default rate of the bank's own portfolio, a finding which is consistent with most bank modelling. The multi-market extension also illustrates that lending should increase as banks diversify to the extent that different sub-markets have default rates are not positively correlated. The extension also illustrates the interaction of variance and covariance terms which can be applied in empirical analysis of risk assessment.

The comparative statics of the model also indicate that lending levels should be increasing in demand conditions and bank market share and decreasing in bank costs, the risk-free rate, and the expected default rate. Cost differentials between banks should also influence lending levels, with more efficient lenders expanding loan volumes and less efficient lenders having smaller loan volumes. To the extent that cost differentials are driven by economies of scale, the absolute size of banks should be positively related to lending levels. The level of lending should be non-decreasing in the bank's level of capitalization.

Risk Measure Derivation and Empirical Modelling

Empirical testing of the theoretical model is done in two stages using data for West Virginia. In the first stage, outlined in detail in the Appendix, a model of a loan loss proxy by sector is estimated, and the residuals from the sectoral equations are used to construct a covariance matrix among sectors. The covariance matrix is transformed to obtain bank-specific scalar risk measures using a weighting procedure based on county industry mixes. The calculated risk measures for banks also incorporates the locational structure of bank branch systems and holding company affiliation. The bank risk measures are the primary independent variables of interest for the second stage, which consists of a series of regression models estimating the percentage of each bank's portfolio in loans or commercial loans as a function of the loss variance, expected default rates, and other independent variables which reflect differences in loan demand, competition, and economies of scale.

Stage I -- Assessing Default Risk

The modelling strategy for determining the riskiness of lending in a particular county is to isolate unpredictable changes which drive loan losses. In order to do this, I use a simple predictive model of state business failure rates for sectors based on lagged values of business failure rates and knowledge of movements in state earnings. The use of only lagged values reflects the predictive nature of the model -- the behavior of interest is of banks making loans with imperfect knowledge of future developments. The underlying model of inter-industry interaction is the economic base model in which basic (export-oriented) sector activity drives non-basic (local or secondary) sector activity.

For each basic sector (agriculture, manufacturing, and mining), business failure rates in each time period are modelled as a function of lagged values of the sector's own rates and lagged state earnings growth rates, to incorporate a state business cycle effect. For each non-basic sector (construction, transportation and public utilities (TPU), wholesale, retail, services, and finance, insurance and real estate (FIR)), failure rates in each time period are modelled as a function of lagged values of the sector's own rate and an aggregate basic sector failure rate.

The loan loss proxy could be one of any number of measures. The most direct measure would be actual loan losses by sector, such as the data available from the Shared Credits data base and used by Chirinko and Guill (1991). This database, however, is collected on a national basis and only includes very large loans. The business failure rate is closely related and is available at the state level. Limited data - - 11 years worth (1984-1994) of business failure data for all states for broad sectors is available from Dun & Bradstreet - - was obtained for use in estimating forecasting models of failure rates by sector for West Virginia.

The use of state-level, rather than county level, data represents a compromise on the geographic scale, but no data series closely related to loan losses exists for counties. Using state data requires the assumption that county failure rates correspond to state rates sector by sector, and that differences in sectoral shares of county income drive differences in default experience among counties.

The available data is monthly, but many months for many sectors show no business failures, so the data has been aggregated to quarters. Since the failure data is provided as numbers of failures rather than rates, the number of firms in different sectors in different states is also necessary. This data was taken from Dun's Census of American Business for 1984-1994.

The failure rate series constructed from the failures data and firm counts are shown in figure 1 and summarized in Table 1. As the graphs illustrate, there appears to be substantial comovement among sectors, with a high failure period for most sectors occurring in the first few years of the sample period. The high failure period was followed by several years of relatively low failure rates, followed by a renewed increase in rates in more recent years. Among the sectors, mining had the highest average failure rate by far, more than twice the rate of the next highest sector. FIR and services had the lowest average failure rates, with the other six sectors clustered at similar values around two failures per quarter for every one thousand firms. Mining also had the highest degree of variation in failure rates, with agriculture a close second. Five of the remaining sectors had standard deviations less than one-third of the mining sector's value.

Each of the failure rate series was initially tested for the presence of a unit root following the procedures outlined in Enders (1995). Each augmented Dickey-Fuller equation, with both a constant and trend term, was fitted to the proper lag length, testing down from a possible 8 lags, using the Schwartz Criterion. Testing then proceeded by considering the appropriateness of including the constant and trend and, within the testing framework, if a unit root existed. In every sector, the presence of a unit root was rejected.

A forecasting model for each of the series was then specified beginning with the continuous lag length indicated in the unit root testing. If strong autocorrelations appeared at higher lags, individual lags were added to the equation. After own lags were included, up to four quarterly lags of the aggregate basic sector failure rate (for the non-basic sectors only) and percentage change in state income were examined and included if the Schwartz Criterion indicated improvement in the model.

After fitting the OLS regressions to the proper lag lengths in a sector's own failure rate, the basic sector failure rate if appropriate, and income growth, each of the models was re-estimated using a Tobit model to account for the zero restriction on failure rates. As expected, the influence was greatest on those sectors with the largest number of zero observations.

Agriculture, a very small sector in West Virginia, was by far the biggest problem with 17 of the original 44 observations at zero.

The final predictive model results are summarized in Table 2. As shown in the table, there was a wide variety of lag length specification between sectors. Agriculture, manufacturing, and services each had a high number of continuous lags. Construction and wholesale, the two sectors with the worst overall fits, had only two own lags included. Basic failure rate lags were included in 5 of the six non-basic sector models. Four of the five coefficients were positive, as expected, although the negative coefficient is statistically significant. The lagged income growth rate added to prediction in only four of the nine sectors, twice each positively and negatively. Using the OLS R^2 as a rough guide to the fit of the models, we observe a range from 0.183 to 0.591, significant but not dramatic results of predictability.

The residuals from the Tobit estimations were recovered and used to calculate conditional variances and covariances. The correlation and covariance matrices among the sectors are shown in Table 3A. These values can be contrasted to the unconditional correlation and covariance matrices, i.e., between the failure rates themselves, shown in Table 3B. The unconditional matrices reveal far more correlation and covariance between the sectors, and all of the covariance terms are positive. The conditional matrices reveal that after prediction is taken into account, very little correlation persists and a few negative, although small, covariances result. Among the persistent positive correlation and covariation is the entire group of non-basic sectors, with the minor exception of a small negative correlation between FIR and services.

The county weighting vectors necessary for converting the state risk matrix to county and bank-level risk measures were derived from an unsuppressed version of the Regional Economic Information System (REIS) of the U.S. Bureau of Economic Analysis. The sectoral earnings measures were adjusted for inflation and then averaged over the 1989-1993 period to avoid severe fluctuation over time, especially in farm income.

The branching structure of banks used in the analysis, i.e., the amount of deposits at each branch bank location, is based upon the Summary of Deposits files produced by the FDIC. These files are available on an annual basis for June 30 and report the amount of deposits at each branch of every branch banking system in the United States. Holding company affiliation was identified in both June 30, 1993 and December 31, 1993. Holding companies with affiliates outside of the state were dropped from the sample, as were those belonging to holding companies which changed affiliates between June and December of 1993. The remaining sample consists of 88 West Virginia banks, roughly one-third each independent, affiliated with single-bank holding companies, and affiliated with multi-bank holding companies.

For each bank in the sample, a neutral-weighted portfolio was constructed using the county industry mix and deposit distribution among counties. In addition, a holding company-wide measure was calculated for each bank in a multi-bank holding company. The portfolio variance measures were then calculated using the procedure outlined in equations (6) - (10) of the Appendix. Expected failure rates, short-run as measured for the fourth quarter of 1993, and long-run as measured using the sector average default rates, were also calculated using the bank neutral-weighted portfolios.

The risk measures varied substantially over the sample of banks, as summarized in Table 4, which shows the descriptive statistics for the risk measures and other variables considered for inclusion in the second stage of modelling. The standardized ("Std." on the table) measures, adjusted to the highest single measure, are more convenient for comparative purposes. The mean holding company-wide failure rate variance was only 14.4 percent of the highest, and the standard deviation confirms a substantial spread of values. In fact, the lowest failure rate variance measures were only about three per cent of the highest. The average short-run expected failure rate was about one-half of the highest, with the lowest rate about one-quarter the highest. The average long-run rate was 45.8% of the highest, with the lowest value at about 38 per cent of the value of the highest.

The risk measures also revealed a general decrease, including some sizable individual decreases in risk, when measured at the holding company level rather than the bank level. As shown in Table 5, of the 28 banks belonging to multi-bank holding companies, seventeen of the banks have lower risk measures when evaluated relative to the holding company, while only nine have increases and two stay the same. In addition, the decreases tend to be much greater than the increases in absolute value terms. Only three of the increases exceed five percent and all are less than twenty-five percent. Six of the decreases are by more than twenty-five percent and an additional nine are between five and twenty-five percent. The most notable risk reduction is for bank 5 in holding company A, where inclusion of holding company diversification reduces the standardized risk measure from 0.392 to 0.089.

When entire holding companies are examined, similarly interesting results can be found. Most notably, there is no uniform effect -- some configurations lead to substantial reductions in failure rate covariance risk, at least in some banks, while others leave risk essentially unchanged. The extreme case of no change is holding company F, where both banks have the same industry mix due to location in the same county. Holding companies B and C also show little change due to holding company configuration. Holding companies A, D, and E appear to have the greatest risk reduction due to the holding company configuration.

Stage II -- Bank Asset Allocation Model Estimation

The modelling of the default risk inherent in lending in different counties is preliminary to estimating the model of asset allocation given the exogenous riskiness. The model of asset allocation is based on not only the default riskiness, but also on other features of banks and banking markets highlighted in the theoretical model and the banking literature. This section describes, in more detail, the specific nature of the dependent and exogenous variables in the estimation.

The dependent variable is the percentage of a bank's assets which is allocated to loans. This measure was calculated based on total asset and net loan dollar amounts reported in the year-end Condition Reports filed by all banks with the Federal Deposit Insurance Corporation. In order to avoid the effect of changes over time in group bank affiliations, simple cross-sectional analysis is used. Data for December 31, 1993 is used to identify bank-related variable values.

The primary exogenous variables are the expected failure rate and failure rate variance measures described above. Both expected failure rate measures, short-run and long-run, are investigated. The bank-level and holding company-wide variance measures are also both considered.

The potential influence of differences in loan demand are also included in the model estimation. Loan demand can vary among local markets for a number of reasons. Borrowers may seek loans from outside of the area if bank lending limits are too low or if establishments may be financed within large corporations headquartered elsewhere. These influences can be measured by including variables for the average number of employees per establishment, which has been derived from data available in County Business Patterns. Differences in firm finance and the use of local banking institutions will also be accounted for by calculating the percentage of county income being earned by proprietors, who are more likely than other firms to seek lending from local banks. This variable can be calculated from the REIS data base discussed above. Finally, the earnings growth rate of the local economy from 1992 to 1993 has been calculated, again using REIS data, to reflect demand for loans.

For each of these variables, all non-branching banks in a particular local economy have been assigned the same value. Banks with branches are assigned values which are weighted averages, according to deposit proportions, of the values in the counties in which the banks are operating. Holding company considerations do not apply to the local economic data.

The total size of the bank, measured by assets, is included to reflect economies of scale which might tend to increase the lending levels of banks by decreasing lending costs and allowing specialization in lending. Such economies are believed to exist but to possibly be exhausted at about a $100 million (see Clark, 1988) level, well above the size of many of the banks in the sample area. The size indicator may also reflect differences in bank risk aversion. In addition to bank size, holding company size is included as an independent variable. The value for independent banks is simply the amount of deposits at the bank, while the holding company value is the amount of deposits held by the entire holding company. In order to capture the probable non-linearity of the economies-of-scale relationship, both the individual bank and bank group measures have been examined, in separate runs, in logarithmic form.

The behavior hypothesized in the structure-conduct-performance and efficient structure literature is also be considered in assessing the effect of default risk on lending. The theoretical model postulates an influence of market share, which will increase lending amounts, but not necessarily loan/asset ratios. Branching effects complicate the use of market share, but weighted average market shares, computed according to proportions of total bank deposits in individual county markets, are used in the empirical estimation. The effects of concentration are not directly addressed in the theoretical model, but are of such wide interest as to warrant inclusion in the empirical model. A weighted average Herfindahl index of market concentration is included to measure market concentration.

Finally, the capitalization level of banks is considered in the empirical estimation. The theoretical discussion indicates that higher capital levels will lead to higher lending levels if return on equity is an important element in determining bank managers' utility. A different perspective evident in some bank literature also postulates a capital effect on lending whereby higher capital levels encourage expanded lending due to a larger buffer against bank failure. Capitalization is included as a variable calculated as capital expressed as a percentage of assets. A measure of capitalization at the holding company level is also be included as an independent variable to reflect the potential influence of decision-making at the holding company level. Bank capital data is available on the FDIC call report tapes.

The empirical model described above is suited not only for examining the effect of a number of influences on total bank lending, but also captures the most important influences on commercial lending as well. In fact, several of the measures, including the risk measures, are better suited to describe differences in commercial lending. To test the model suitability for commercial lending, an additional set of models have been estimated with the same independent variables and the dependent variable business loans as a percentage of total assets. The measure of business lending is an aggregation of several categories on the FDIC call reports.

The summary of descriptive statistics for the modelled variables is in Table 4. The long-run expected failure rate measure is similar to the short-run measure, discussed above, but has a higher mean and smaller spread. The percentage of earnings to proprietors averages about thirteen percent but varies between five and twenty-nine percent. Employees per establishment varies between five and twenty-two. Market share and the Herfindahl index vary similarly, both reaching a high of 1.0 in a one-bank county. The average size of bank in the sample is a little over $100 million in assets, but the range is from $10 million to $1.5 billion. Holding company assets range as high as almost three billion dollars. Capital asset ratios average ten percent, with a low of 5.5 percent, but the ratios go as high as 24.3 per cent, extremely high by industry standards. The dependent variable loan/asset ratio averages 0.52, about half of assets in loans, with a low of only 0.12 and a high of almost 0.8. The business loan/asset ratio averages about 0.15, with a low near zero and a high of 1/3 of assets.

The model estimations are shown in Tables 6 (for the loan/asset ratio) and 7 (for the business loan/asset ratio). It is immediately apparent that the full group of independent variables is not included in any of the reported models. This discrepancy is due to very high multicollinearity among the variables with condition numbers on the order of 70 to 80 in the full models. Given the ill-conditioning and the weaker theoretical links of particular variables, the models were fitted without the capital/asset ratio variables (which may also raise simultaneity questions), employees per establishment, bank-level variance, and bank asset variables.

The five models listed illustrate the key findings of the second stage analysis. Models 1 and 2 include both the expected short-run failure rate and the failure rate variance. They vary only in which holding company asset variable is used. In both cases, the asset size variable is positive and significant and the holding company-wide variance measure is negative and significant. However, the expected failure rate coefficient is positive. The positive expected failure sign and negative variance sign are probably reflecting the high correlation (0.91) between the two measures. In effect, the West Virginia failure rate models identify a single dominant dimension, largely related to the presence of the mining sector, that drives both risk measures. The long-run expected failure rate measure (Model 3) produces similar results when included with the failure rate variance.

The final two models were run to investigate the effect of either risk measure in the absence of the other. Both models use log of assets due to its better fit and consistency with theory and earlier empirical work. In addition, both models drop the market share variable, which is highly collinear with the Herfindahl index. In each of the two models, the risk variable has a negative and significant effect and the size variable has a positive and significant effect. None of the other variables is significant. All three, however, enter with a sign opposite what was expected. This result is consistent with other model variants including only one risk measure. In those models, not reported here, the coefficient on the risk variables appears to be very robust to the specification of the demand and market characteristics.

The business loan models, using the same variants as the loan/asset ratio, do not perform as well as the loan/asset model. All but Model 4 are, however, significant at the 95% level. In terms of the influence of the different variables, the interpretation is virtually identical to the loan/asset case: negative and significant risk variables, positive and significant size variables, and insignificant with the wrong sign demand and market power variables.

Conclusion

The empirical work illustrates an alternative measure for assessing risk at banks which includes county-specific industrial mix characteristics and locational characteristics of bank groups. The holding company risk measures reveal potential trouble with using simplified measures such as dummy variables indicating inclusion in multi-bank holding companies, since the risk effects of holding company inclusion vary according to particular situations. The risk measures also clearly illustrate substantial intrastate variation in risk among different banks in different county lending environments. While this brings into doubt suggestions to adjust deposit premia based upon state risk characteristics, it also provides a potential avenue for calculating more appropriate risk measures.

The second stage results are encouraging given their findings of an important negative risk effect, along with the expected size effect. The incorrect signs on other variables is troubling, perhaps reflecting some omitted variable bias, but their lack of statistical significance lessens the concern. The finding of no important effect of market structure characteristics is an important one in light of previous findings that market structure may have an influence on lending levels.

Appendix -- Assessing Default Risk

The modelling strategy for determining the riskiness of lending in a particular county is to isolate unpredictable changes which drive loan losses and correlate the changes among sectors. Although the specifics of the application differ, the approach follows closely from Neumann and Topel's (1991) technique for examining unemployment and diversification. In this setting, I use a simple predictive model of loan loss trends (proxied by business failure rates) for industries in individual counties based on lagged values of loan losses and knowledge of movements in state economic activity. The use of only lagged values reflects the predictive nature of the model -- the behavior of interest is of banks making loans with imperfect knowledge of future developments. The underlying model of inter-industry interaction is the economic base model in which basic (export-oriented) sector activity drives non-basic (local or secondary) sector activity.

For each basic sector, loan losses in each time period are modelled as a function of lagged values of the sector's own loan losses and lagged earnings growth rates, denoted GSP, to incorporate a state business cycle effect. For each non-basic sector, loan losses in each time period are modelled as a function of lagged values of the sector's own loan losses and total basic sector loan losses. A total of N ($=n_1+n_2$) time series equations are estimated, one for each of n_1 basic sectors and n_2 non-basic sectors. The structure of each basic and non-basic equation is as follows:

$$(1) \qquad B_{q,t} = \alpha_q + \sum_{\tau=1}^{T_q} \beta_{q\tau} B_{q,t-\tau} + \sum_{\tau=1}^{T_G} \gamma_{q\tau} GSP_{t-\tau} + \varepsilon_{q,t}\ , \qquad q = 1,\dots,n_1$$

$$(2) \qquad N_{r,t} = \alpha_r + \sum_{\tau=1}^{T_r} \beta_{r\tau} N_{r,t-\tau} + \sum_{\tau=1}^{T_r'} \delta_{r\tau} B'_{t-\tau} + \sum_{\tau=1}^{T_G} \gamma_{r\tau} GSP_{t-\tau} + \varepsilon_{r,t}\ , \qquad r = n_1+1,\dots,n_2$$

where $B_{q,t}$ is the level of the loan loss indicator for basic sector q at time t,

$N_{r,t}$ is the level of the loan loss indicator for non-basic sector r at time t,

T_q and T_r indicate the number of lags of a given sector's loan losses on itself,

T_r' indicates the number of lags of basic sector
loan losses in the non-basic sector r equation,

T_G indicates the number of lags on GSP, and

B' indicates an aggregate loan loss indicator for the basic sectors.

The result of the time series estimations are error vectors ε_i over time for each sector i :

$$(3) \qquad \varepsilon_{si} = \begin{bmatrix} \varepsilon_{si1} \\ \varepsilon_{si2} \\ \cdot \\ \cdot \\ \cdot \\ \varepsilon_{siT} \end{bmatrix}, \quad i = 1,\ldots,N.$$

The parameter T indicates the total number of time periods. The error vectors specified in (3) are used to calculate the intrastate intersectoral variance-covariance matrix Ω:

$$(4) \qquad \Omega = \begin{bmatrix} \sigma_{11} & \sigma_{12} & \cdots & \sigma_{1N} \\ \sigma_{21} & \sigma_{22} & \cdots & \sigma_{2N} \\ \cdot & \cdot & \cdots & \cdot \\ \cdot & \cdot & \cdots & \cdot \\ \sigma_{N1} & \sigma_{N2} & \cdots & \sigma_{NN} \end{bmatrix},$$

$$where \quad \sigma_{ij} = \frac{1}{T}\varepsilon_i'\varepsilon_j.$$

Given a covariance matrix Ω, gauging default risk in counties requires a weighting scheme for sectors to indicate their relative sizes in the bank's loan portfolio. I use the concept of a neutral-weighted portfolio, i.e., one weighted according to the proportions of economic activity in given sectors, for this purpose. This assumes that banks will hold portfolios with proportions roughly equivalent to sectors' levels of income in the county economy and that personal and real estate loan proportions also roughly correspond to these proportions. The neutral-weighted portfolio in county *c* is described by the weight vector Λ_c:

$$(5) \qquad \Lambda_c = \frac{1}{\sum_{i=1}^{N} X_{ci}} \begin{bmatrix} X_{c1} \\ X_{c2} \\ \cdot \\ \cdot \\ \cdot \\ X_{cN} \end{bmatrix},$$

where X_{ci} is the level of economic activity in sector *i* of county *c*. Although banks do not compose their portfolios in exact proportion to the county's economic activity, and other weighting schemes might be envisioned, the neutral-weighted portfolio is a reasonable approximation.

The final step in assessing the risk of lending at a particular bank involves using the county weighting vectors, intrastate covariance matrices, and deposit amounts to derive a scalar measure of default risk $BRISK_b$ relevant to each individual bank *b*. The particular measure will vary according to the locational and holding company affiliation characteristics of each bank. Three particular cases can arise. The first case consists of banks for which all banking offices and holding company affiliate offices are in the same county. This includes unit banks, independent banks and single-bank holding company affiliates with all branches limited to a single county, and multi-bank holding company affiliates where all branches of all affiliates are in the same county. The second case consists of independent banks and single-bank holding company affiliates with branches in multiple counties. The third case consists of multi-bank holding comany affiliates where offices exist in more than one county.

The first case, with operations limited to a single county, is straightforward and involves only the intrastate covariance matrix and county weighting vector relevant to the bank. The measure $BRISK_b$ in this case is calculated as:

$$(6) \qquad BRISK_b = \Lambda_c^{\prime}\Omega\Lambda_c.$$

Given the definitions of the covariance matrix and the weighting vector, the $BRISK_b$ measure is the variance of the loan portfolio default rate from the point of view of a bank operating only in county *c* whose loans are held in proportion to those sectors' proportions of county economic activity.

The second case, single-bank organizations with branches in multiple counties, also requires state matrices and county weighting vectors but also considers the deposit distribution at different locations within a state, thus more accurately measuring the effects of geographical diversification upon default risk for branch systems. For any particular combination of counties, the appropriate measure of risk $BRISK_b$ is

$$(7) \qquad BRISK_b = \Lambda_b^{\prime}\Omega\Lambda_b.$$

where

$$(8) \qquad \Lambda_b = \sum_{c=1}^{C} \frac{D_{bc}}{\sum_{k=1}^{C} D_{bk}} \Lambda_c$$

Equation (8) defines the neutral-weighted portfolio of a multi-county bank as a weighted average of the neutral-weighted portfolios of the individual counties, where the weights are the fractions of deposits obtained from the respective counties. The expression D_{bc} indicates the amount of deposits at bank *b* which are generated at branches in county *c*, and *C* indicates the total number of counties in the state.

Given the definitions of the variance-covariance matrix and the weighting vector, the $BRISK_b$ measure in equation (7) is the variance of the loan portfolio default rate from the point of view of a branch system with banks in multiple counties whose loans are held in proportion to sectors' proportions of county economic activity in each county. The proportion of lending in a given county is assumed to be equal to the proportion of the bank's deposit holdings which are in the county. In the case of a bank with no branches or branches only within a single county, equation (8) reduces to Λ_c and the simple county risk expression (6) applies.

The preceding discussion indicates the assignment of portfolio variance risk measures to individual banks based upon the location of the bank's branches. Further extension is necessary to explore holding company diversification opportunities and their effect on lending at individual banks. For a holding company affiliate, we need a method of combining the variance of an individual affiliate bank with covariance measures between the particular affiliate and the other affiliates in the holding company banks. These are the relevant measures as indicated in the two-market case illustrated in the theoretical discussion in Sorenson(1995), which shows that marginal risk in a multi-market context includes the default risk variance for the bank and the covariance between that bank and the other holding company affiliates, assuming that optimization is done at the holding company level, rather than at each individual affiliated bank. The variances and covariances are weighted by the amount of lending done in the respective markets.

Rather than use the endogenous lending amounts for weighting the variances and covariances, I use deposits, which have a close relation to lending amounts, to indicate the weights to be given the bank risk measures. Specifically, weights of the different banks are determined by the shares of holding company deposits at the various banks.

We shall use the term D_d to refer to deposits of bank d which are controlled by a given bank b's holding company. D_d takes on a value of 0 for all banks not affiliated with bank b's holding company and a value equal to the entire amount of bank deposits for affiliates of bank b's holding company. Given this notation, we can specify the bank-specific risk measure $BRISK_b$ for a bank b within a particular holding company as the following weighted average of default rate covariances between the individual bank and each bank in the holding company:

$$(9) \qquad BRISK_b = \sum_{d=1}^{B} \frac{D_d}{\sum_{d=1}^{B} D_d} COV_{b,d}$$

where

$$(10) \qquad COV_{b,d} = \Lambda_b' \Omega \Lambda_d.$$

The resulting covariance measures from (10) are summed over all holding company affiliates weighted according to the proportion of holding company deposits in each bank as shown in equation (9). The fractional part of equation (9) is simply the proportion of holding company deposits held at bank d, the weighting factor which describes the approximate proportion of the holding company portfolio to which the covariance $COV_{b,d}$ applies. The weight is applied to the covariance between the particular bank b and bank d via multiplication as shown in the equation. The leading summation indicates that the weighted average is constructed over all banks in the holding company.

In summary, note that equation (9) is completely general if independent banks are thought of as belonging to their own holding company. For independent banks without branches, $BRISK_b$ reduces to the original single-county measure shown in equation (6). For single-bank organizations with branches in multiple counties, $BRISK_b$ in equation (9) reduces to the branch measure shown in equation (7). For holding company affiliates, the variance portion of the $BRISK_b$ measure, i.e., $COV_{b,b}$, will correspond to either the equation (6) or equation (7) value, and the covariance measures will be calculated according to equation (10).

The use of different measures for branching systems (equation 7) and holding company banks (equation 9) is somewhat artificial, resulting largely from data limitations under which branch systems report loan information only at the bank level, not at the branch level. The specification explicitly allows for different risk measures at different holding company affiliates, but does not obviously address the likelihood of different risk situations at different branches of a branch bank system. It should be noted, however, that the branch expression (7) is equivalent to performing the holding company analysis of equations (9) and (10) for each branch and then weighting the resulting risk measures according to overall bank deposit shares to achieve a single risk measure. It is reasonable to assume the individual branches may be viewed differently by bank managers as they contribute differentially to overall portfolio variance, in which case lending might not be distributed according to deposit proportions. It can be expected, however, that there are limits to increasing lending in particularly attractive markets (price effects) and decreasing lending in unattractive markets (customer service obligations), so that the technique proposed, which essentially combines attractive and unattractive markets, yields an acceptable measure of branch bank risk.

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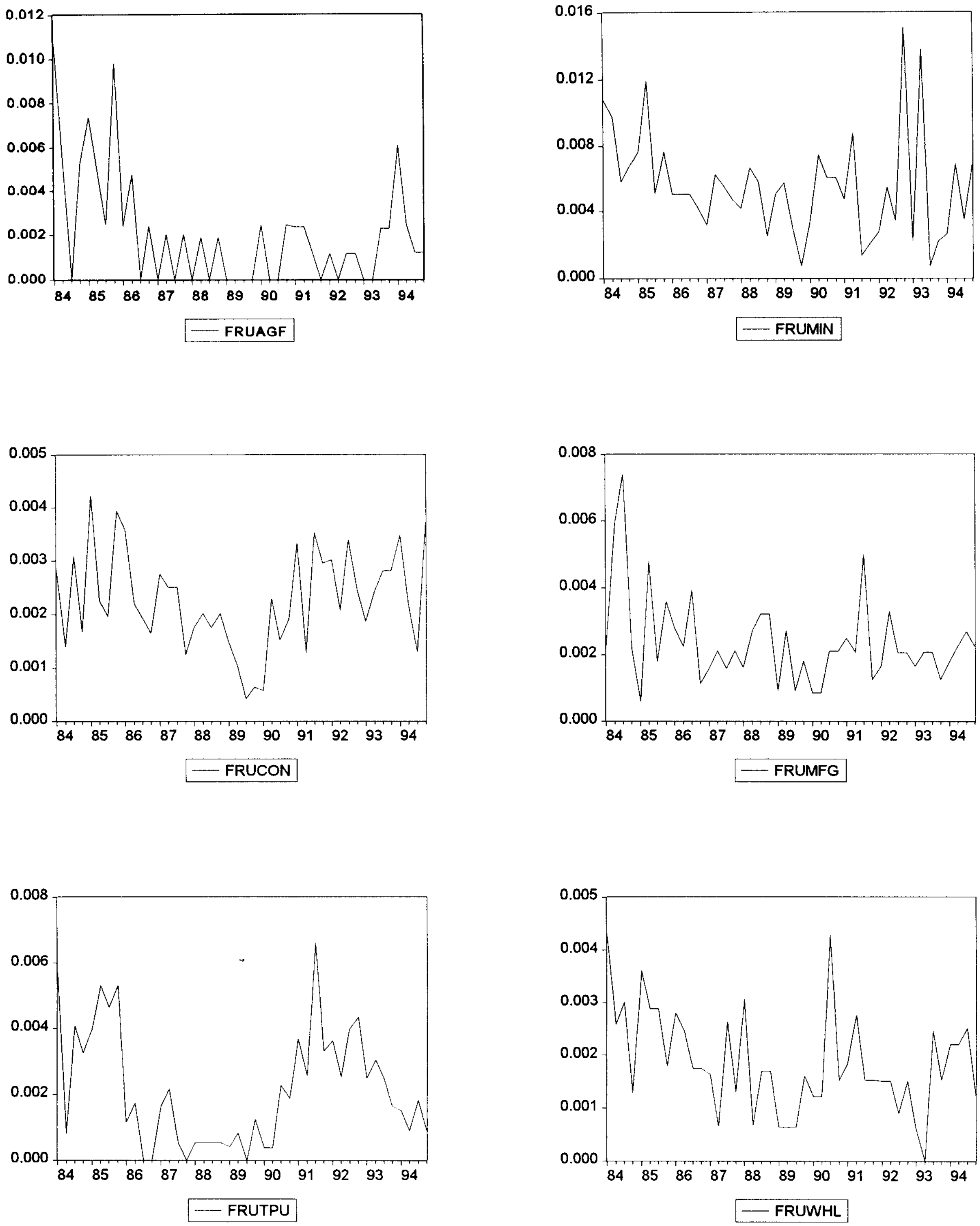
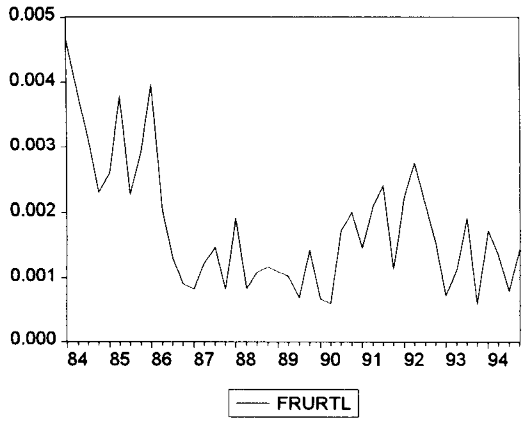
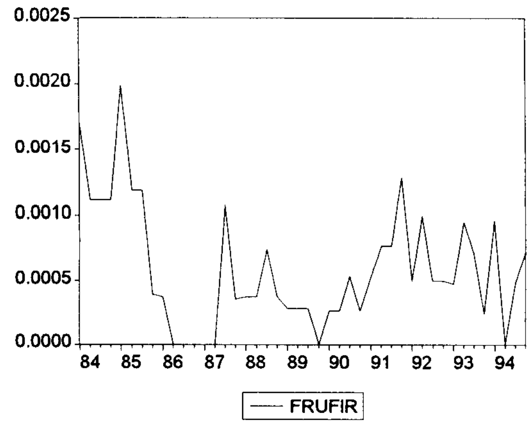
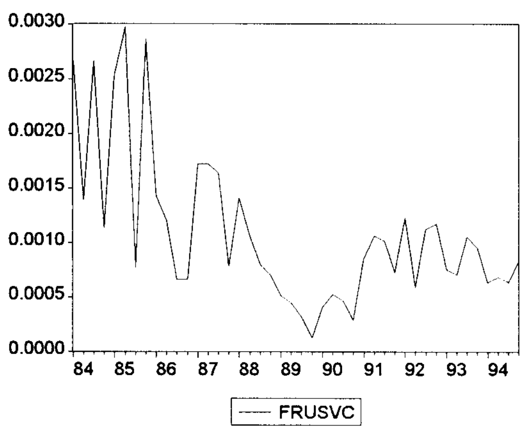
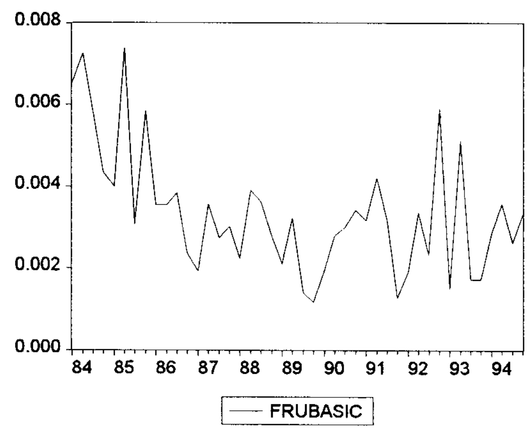
Figure 1. Quarterly Sectoral Failure Rates for West Virginia, 1984-1994











Key:		
	FRUAGF	Failure Rate for Agriculture, Ag. Services, Forestry, and Fisheries
	FRUMIN	Failure Rate for Mining
	FRUCON	Failure Rate for Construction
	FRUMFG	Failure Rate for Manufacturing
	FRUTPU	Failure Rate for Transportation and Public Utilities
	FRUWHL	Failure Rate for Wholesale Trade
	FRURTL	Failure Rate for Retail Trade
	FRUFIR	Failure Rate for Finance, Insurance, and Real Estate
	FRUSVC	Failure Rate for Services
	FRUBASIC	Failure Rate for Combined Agriculture, Mining, and Manufacturing

Table 1. Descriptive Statistics for Failure Rates, WV 1984-1994

	Mean	Std. Devn.	Maximum	Minimum
Agriculture	0.002114	0.002595	0.010667	0.000000
Mining	0.005542	0.003175	0.015110	0.000722
Construction	0.002275	0.000916	0.004225	0.000426
Manufacturing	0.002386	0.001348	0.007396	0.000598
TPU	0.002170	0.001760	0.006625	0.000000
Wholesale	0.001872	0.000964	0.004305	0.000000
Retail	0.001776	0.000989	0.004626	0.000601
FIR	0.000594	0.000470	0.001987	0.000000
Services	0.001087	0.000706	0.002973	0.000128

Table 2. Summary of Tobit Predictive Models for Failure Rates by Sector in West Virginia

Sector	Own Lags	Basic Sector Failure Rate Lags	Income Growth Rate Rate Lags	Quarters with Zero Failures	Log-likelihood Function Value	Likelihood Ratio Statistic	LR Statistic Chi Square Significance
Agriculture	1-8		2 (Neg.*)	15	95.901	21.568	0.010354
Mining	1,2,8		2 (Pos.)	0	164.514	13.016	0.011198
Construction	1,2	2 (Pos.)	1 (Neg.)	0	238.648	8.588	0.072264
Manufacturing	1-9			0	206.138	18.672	0.028131
TPU	1,2,8	4 (Neg.**)		4	168.432	25.030	0.000050
Wholesale	1,2	1 (Pos.*)		1	231.798	8.508	0.036601
Retail	1-4	3 (Pos.***)	3 (Pos.)	0	245.615	35.660	0.000003
FIR	1-5	1 (Pos.)		7	204.939	19.846	0.002950
Services	1-8			0	240.110	17.966	0.021483

Notes:
The lag columns indicate which specific lags are included, not the number of lags.
Neg. indicates that a lag entered with a negative coefficient; Pos. indicates that a lag entered with a positive coefficient..
, **, and * indicate chi square significance at the 10%, 5%, and 1% levels, respectively*

Table 3A. CORRELATIONS AND COVARIANCES BETWEEN FAILURE RATE RESIDUALS, WV 1984-1994

Correlations:

NAME	TRESAGF	TRESMIN	TRESCON	TRESMFG	TRESTPU	TRESWHL	TRESRTL	TRESFIR	TRESSVC
TRESAGF	1.00	0.01	0.29	-0.04	-0.02	0.13	-0.14	0.05	0.16
TRESMIN	0.01	1.00	-0.04	0.00	0.05	0.01	0.09	0.20	0.08
TRESCON	0.29	-0.04	1.00	0.16	0.34	0.06	0.20	0.16	0.44
TRESMFG	-0.04	0.00	0.16	1.00	0.43	-0.12	0.17	0.06	0.03
TRESTPU	-0.02	0.05	0.34	0.43	1.00	0.00	0.20	0.02	0.44
TRESWHL	0.13	0.01	0.06	-0.12	0.00	1.00	0.43	0.07	0.09
TRESRTL	-0.14	0.09	0.20	0.17	0.20	0.43	1.00	0.09	0.27
TRESFIR	0.05	0.20	0.16	0.06	0.02	0.07	0.09	1.00	-0.09
TRESSVC	0.16	0.08	0.44	0.03	0.44	0.09	0.27	-0.09	1.00

Covariances:

NAME	TRESAGF	TRESMIN	TRESCON	TRESMFG	TRESTPU	TRESWHL	TRESRTL	TRESFIR	TRESSVC
TRESAGF	1.14	0.04	0.26	-0.03	-0.03	0.11	-0.07	0.02	0.05
TRESMIN	0.04	6.46	-0.09	0.00	0.13	0.02	0.11	0.15	0.06
TRESCON	0.26	-0.09	0.69	0.09	0.28	0.04	0.09	0.04	0.11
TRESMFG	-0.03	0.00	0.09	0.45	0.28	-0.07	0.06	0.01	0.01
TRESTPU	-0.03	0.13	0.28	0.28	1.02	0.00	0.10	0.01	0.14
TRESWHL	0.11	0.02	0.04	-0.07	0.00	0.66	0.18	0.02	0.02
TRESRTL	-0.07	0.11	0.09	0.06	0.10	0.18	0.28	0.01	0.04
TRESFIR	0.02	0.15	0.04	0.01	0.01	0.02	0.01	0.09	-0.01
TRESSVC	0.05	0.06	0.11	0.01	0.14	0.02	0.04	-0.01	0.10

Table 3B. CORRELATIONS AND COVARIANCES BETWEEN FAILURE RATES, WV 1984-1994

Correlations:

NAME	FRUAGF	FRUMIN	FRUCON	FRUMFG	FRUTPU	FRUWHL	FRURTL	FRUFIR	FRUSVC
FRUAGF	1.00	0.31	0.35	0.09	0.42	0.42	0.60	0.41	0.59
FRUMIN	0.31	1.00	0.06	0.20	0.26	0.13	0.36	0.33	0.39
FRUCON	0.35	0.06	1.00	0.13	0.54	0.19	0.38	0.36	0.53
FRUMFG	0.09	0.20	0.13	1.00	0.30	0.20	0.52	0.19	0.39
FRUTPU	0.42	0.26	0.54	0.30	1.00	0.28	0.58	0.55	0.56
FRUWHL	0.42	0.13	0.19	0.20	0.28	1.00	0.61	0.46	0.47
FRURTL	0.60	0.36	0.38	0.52	0.58	0.61	1.00	0.56	0.66
FRUFIR	0.41	0.33	0.36	0.19	0.55	0.46	0.56	1.00	0.47
FRUSVC	0.59	0.39	0.53	0.39	0.56	0.47	0.66	0.47	1.00

Covariances:

NAME	FRUAGF	FRUMIN	FRUCON	FRUMFG	FRUTPU	FRUWHL	FRURTL	FRUFIR	FRUSVC
FRUAGF	6.73	2.54	0.84	0.30	1.94	1.06	1.53	0.50	1.08
FRUMIN	2.54	10.08	0.18	0.85	1.48	0.40	1.12	0.49	0.88
FRUCON	0.84	0.18	0.84	0.17	0.86	0.17	0.34	0.16	0.34
FRUMFG	0.30	0.85	0.17	1.82	0.70	0.27	0.70	0.12	0.37
FRUTPU	1.94	1.48	0.86	0.70	3.10	0.48	1.00	0.45	0.70
FRUWHL	1.06	0.40	0.17	0.27	0.48	0.93	0.58	0.21	0.32
FRURTL	1.53	1.12	0.34	0.70	1.00	0.58	0.98	0.26	0.46
FRUFIR	0.50	0.49	0.16	0.12	0.45	0.21	0.26	0.22	0.16
FRUSVC	1.08	0.88	0.34	0.37	0.70	0.32	0.46	0.16	0.50

Table 4. Descriptive Statistics for Variables

Variable	Mean	Std Dev	Minimum	Maximum
Long-run Expected F.R.	0.00235	0.000638	0.00166	0.00431
Std. Long-run Expected F.R.	0.5458	0.1481	0.3846	1.0000
Short-run Expected F.R.	0.00208	0.000816	0.00114	0.00460
Std. Short-run Expected F.R.	0.4530	0.1774	0.2490	1.0000
Bank-level F.R. Variance	4.668E-7	6.134E-7	1.027E-7	3.086E-6
Std. Bank-level F.R. Variance	0.1513	0.1988	0.0333	1.0000
HC-level F.R. Variance	4.444E-7	6.097E-7	9.707E-8	3.086E-6
Std. HC-level F.R. Variance	0.1440	0.1976	0.0315	1.0000
% Earnings to Proprietors	0.1275	0.0467	0.0534	0.2908
Employees per establishment	11.5795	3.0267	5.1684	22.3783
Earnings Growth Rate 1992-93	0.0194	0.0602	-0.2067	0.2666
Market Share of Deposits	0.3206	0.1948	0.0271	1.0000
Herfindahl Index (of Deposits)	0.3366	0.1447	0.1808	1.0000
Bank Assets ($000s)	108473	173902	10196.0	1523967
Independent Bank (0/1)	0.3750	0.4869	0	1.0000
Single-bank HC Member (0/1)	0.3068	0.4638	0	1.0000
Multi-bank HC Affiliate (0/1)	0.3182	0.4684	0	1.0000
Loan/Asset Ratio	0.5207	0.1492	0.1242	0.7959
Business Loan/Asset Ratio	0.1544	0.0754	0.0185	0.3300
Bank Capital/Asset Ratio	0.1008	0.0309	0.0554	0.2431
Holding Company Assets ($000s)	383579	789793	10196.0	2818008
HC Capital/Asset Ratio	0.1007	0.0302	0.0554	0.2431
Log(bank assets)	11.1728	0.8209	9.2298	14.2368
Log(HC assets)	11.6930	1.3448	9.2298	14.8515

Table 5. Bank-level and Holding Company-wide Failure Rate Variance Measures

Bank	HC	Bank-level Variance	HC-wide Variance	Std. Bank-level Variance	Std. HC-wide Variance
1	A	0.000000112	0.000000117	0.036	0.038
2	A	0.000000340	0.000000181	0.110	0.059
3	A	0.000000105	0.000000100	0.034	0.033
4	A	0.000000122	0.000000126	0.040	0.041
5	A	0.000001208	0.000000275	0.392	0.089
6	A	0.000000318	0.000000181	0.103	0.059
7	A	0.000000104	0.000000107	0.034	0.035
8	A	0.000000116	0.000000110	0.038	0.036
9	B	0.000000183	0.000000213	0.059	0.069
10	B	0.000000390	0.000000326	0.126	0.106
11	B	0.000000183	0.000000213	0.059	0.069
12	B	0.000000368	0.000000312	0.119	0.101
13	C	0.000000421	0.000000423	0.136	0.137
14	C	0.000000436	0.000000430	0.141	0.139
15	D	0.000000374	0.000000255	0.121	0.083
16	D	0.000000123	0.000000148	0.040	0.048
17	D	0.000000196	0.000000130	0.063	0.042
18	D	0.000000115	0.000000097	0.037	0.031
19	E	0.000000183	0.000000152	0.059	0.049
20	E	0.000000779	0.000000492	0.252	0.160
21	F	0.000001170	0.000001170	0.379	0.379
22	F	0.000001170	0.000001170	0.379	0.379
23	G	0.000000205	0.000000187	0.066	0.061
24	G	0.000000238	0.000000196	0.077	0.064
25	G	0.000000168	0.000000148	0.054	0.048
26	H	0.000000116	0.000000119	0.038	0.039
27	H	0.000000447	0.000000336	0.145	0.109
28	H	0.000000116	0.000000119	0.038	0.039

Summary of Bank-level and Holding Company Level Risk Measures

Variable	Mean	Std Dev	Minimum	Maximum
Bank-level F.R. Variance	3.502E-7	3.315E-7	1.04E-7	1.208E-6
HC-level F.R. Variance	2.798E-7	2.739E-7	9.707E-8	1.17E-6
Std. Bank-level F.R. Variance	0.1135	0.1074	0.0337	0.3915
Std. HC-level F.R. Variance	0.0907	0.0888	0.0315	0.3793

Note: Both standardized measures are scaled to the same value.

Table 6. Regression Results for Loan/Asset Ratio.

Variable	Model 1	Model 2	Model 3	Model 4	Model 5
Intercept	-0.0062 *(-0.04)*	0.4760 *(5.93***)*	-0.0528 *(-0.32)*	0.0719 *(0.50)*	0.0602 *(0.45)*
Short-run Expected Failure Rate	63.268 *(1.48)*	54.939 *(1.25)*		-33.762 *(-1.92*)*	
Long-run Expected Failure Rate			66.728 *(1.21)*		
Holding Company-level Failure Rate Variance	-142021 *(-2.48**)*	-128621 *(-2.16**)*	-128367 *(-2.22**)*		-64305 *(-2.78***)*
% Earnings to Proprietors	-0.5727 *(-1.39)*	-0.4190 *(-0.98)*	-0.5409 *(-1.31)*	-0.4335 *(-1.05)*	-0.4876 *(-1.21)*
Earnings Growth Rate 1992-93	-0.3587 *(-1.18)*	-0.3357 *(-1.08)*	-0.3851 *(-1.27)*	-0.4663 *(-1.54)*	-0.4341 *(-1.46)*
Market Share of Deposits	0.0677 *(0.52)*	0.0095 *(0.07)*	0.0601 *(0.47)*		
Herfindahl Index	-0.0321 *(-0.18)*	0.0547 *(0.30)*	-0.0240 *(-0.14)*	0.0532 *(0.49)*	0.0509 *(0.48)*
Holding Company Assets ($000s)		6.75E-8 *(3.57***)*			
Log(Holding Company Assets)	0.0451 *(4.16***)*		0.0461 *(4.25***)*	0.0484 *(4.39***)*	0.0464 *(4.29***)*
R^2	.3041	.2696	.2978	.2505	.2844
F Prob>F	4.994 *0.0001*	4.217 *0.0005*	4.846 *0.0001*	5.482 *0.0002*	6.517 *0.0001*
Condition Number	33.03	20.40	37.38	29.24	27.46

NOTES: All regressions were run using a sample of 88 West Virginia Banks.
The figures in parentheses are t-statistics.
****, **, and * indicate significance at the 99, 95, and 90 levels, respectively.*
For independent banks and single-bank holding company affiliates, the 'holding company' variables refer to the single bank, i.e., assets for the individual bank only and risk measured according to the industrial composition of the single bank's market area(s) as detailed in the Appendix.

Table 7. Regression Results for Business Loan/Asset Ratio.

Variable	Model 1	Model 2	Model 3	Model 4	Model 5
Intercept	-0.0085 *(-0.11)*	0.1082 *(2.50**)*	-0.0366 *(-0.40)*	0.0404 *(0.52)*	0.0356 *(0.48)*
Short-run Expected Failure Rate	36.177 *(1.55)*	35.576 *(1.49)*		-18.145 *(-1.88*)*	
Long-run Expected Failure Rate			39.019 *(1.29)*		
Holding Company-level Failure Rate Variance	-80147 *(-2.56**)*	-79569 *(-2.48**)*	-73168 *(-2.31**)*		-35781 *(-2.82***)*
% Earnings to Proprietors	-0.2166 *(-0.96)*	-0.1901 *(-0.83)*	-0.1988 *(-0.88)*	-0.1703 *(-0.75)*	-0.2010 *(-0.91)*
Earnings Growth Rate 1992-93	-0.0697 *(-0.42)*	-0.0502 *(-0.30)*	-0.0844 *(-0.51)*	-0.1075 *(-0.65)*	-0.0898 *(-0.55)*
Market Share of Deposits	-0.0125 *(-0.18)*	-0.0220 *(-0.33)*	-0.0165 *(-0.23)*		
Herfindahl Index	0.0885 *(0.93)*	0.1044 *(1.08)*	0.0926 *(0.97)*	0.0830 *(1.39)*	0.0819 *(1.41)*
Holding Company Assets ($000s)		1.20E-8 *(1.17)*			
Log(Holding Company) assets)	0.0108 *(1.83*)*		0.0114 *(1.92*)*	0.0126 *(2.09**)*	0.0115 *(1.94**)*
R^2	.1861	.1665	.1788	.1159	.1596
F Prob>F	2.613 *0.0176*	2.284 *0.0358*	2.488 *0.0231*	2.150 *0.0676*	3.115 *0.0127*
Condition Number	33.03	20.40	37.38	29.24	27.46

NOTES: All regressions were run using a sample of 88 West Virginia Banks.
The figures in parentheses are t-statistics.
****, **, and * indicate significance at the 99, 95, and 90 levels, respectively.*
For independent banks and single-bank holding company affiliates, the 'holding company' variables refer to the single bank, i.e., assets for the individual bank only and risk measured according to the industrial composition of the single bank's market area(s) as detailed in the Appendix.