Loan Portfolio Risk and Capital Adequacy: A New Approach to Evaluating the Riskiness of Banks

Abstract: We develop a *Loan Portfolio Risk (LPR)* variable that measures time-varying volatility in default risk for a portfolio of bank loans. An *Equity-to-LPR* ratio (*ELPR*) is incrementally important in predicting bank failure up to five years in advance, even after controlling for all the CAMELS variables. Publicly-listed banks with higher *ELPR* have lower market implied costs-of-capital. *ELPR* also strongly predicts cross-sectional stock returns under stress conditions. During the financial crisis (7/2007-6/2011), a cash-neutral strategy that longs high-*ELPR* and shorts low-*ELPR* banks yields a monthly alpha of 3.3% to 4.2%. We conclude *LPR* captures key aspects of bank risk missed by a risk-weighted-asset approach.

Keywords: financial statement analysis, bank failure prediction, risk-weighted assets, riskiness of banks, financial crisis, capital adequacy, loan default contagion, market efficiency

JEL Classifications: E32, G14, G21, K23, M41, M48

1. Introduction

The adequacy of a bank's equity capital is of paramount importance, not only to banks, but also to society at large. As the recent financial crisis made painfully clear, financial institutions with inadequate capital can inflict extensive harm beyond the direct losses suffered by their investors. To prevent under-capitalized banks from imposing such negative externalities on society, regulators around the globe have established a relatively uniform set of guidelines and metrics to assess the capital adequacy of these financial institutions.

Most of these capital adequacy regulations have been initiated or inspired by the work of the Basel Committee on Banking Supervision (BCBS). The members of this committee are central banks and financial regulators drawn from 28 jurisdictions. Although the BCBS does not have formal supranational authority and its standards do not have legal force, BCBS member countries generally incorporate its standards into their national regulations. Many non-member countries also adopt or are substantially influenced by the Basel standards.[1]

Central in these standards is the notion of a "**capital adequacy ratio**" (CAR). This ratio is used when determining banks' minimum capital requirements, as well as in the ongoing monitoring and supervision of banks worldwide. Banks typically are required to compute their CAR based on pre-specified rules and report the details of these computations to regulators on a quarterly basis. When a bank's CAR falls below certain thresholds, regulators can take a variety of "prompt corrective actions" (PCAs) against it. Such actions typically involve some form of regulatory intervention, such as restrictions on capital distributions and management fees, restrictions on the growth of certain assets, etc. Banks with extremely low CAR scores are deemed "Critically Undercapitalized" and can be taken into conservatorship (see Appendix II).

[1] Three sets of pronouncements have been issued by the BCBS over time: Basel I (issued in 1988); Basel II (issued in 2004); and the post financial crisis enhancements commonly referred to as Basel III (issued in 2010). We present a timeline and an overview of these pronouncements in Appendix I.

Although the specific details of the CAR calculation have evolved over time, the basic concept is straightforward. Banks are required to hold a minimum amount of regulatory capital in relation to their risk-weighted assets (RWA). Specifically,

$$CAR = \frac{Capital - Adjustments}{Risk\ Weighted\ Assets} \tag{1}$$

Intuitively, the numerator is a measure of the amount of equity capital in the bank; the denominator is a measure of the delinquency risk associated with the bank's assets. Taken as a whole, the ratio is intended to capture the adequacy of a bank's equity capital as a function of its risk exposure to loan defaults.

Over the years, the numerator of this ratio has been largely non-controversial, as commonly-used measures of regulatory capital are all highly correlated with book equity.[2,3] On the other hand, the denominator (i.e., the computation of a bank's "Risk Weighted Assets" or "RWA"), has been the subject of considerable regulatory and academic debate.

The RWA calculation under Basel guidelines involves the grouping of bank investment holdings into different asset classes or "risk buckets." For example, the U.S. adoption of Basel I grouped bank assets into four categories, each with its own risk weighting: sovereign debts (0%), receivables from other banks (20%),

[2] Under the Basel guidelines, the numerator is typically book equity plus adjustments. For example, so-called "Tier-1" or "Core" capital is shareholders' equity plus/minus disclosed reserves. "Tier-2" or "Secondary" capital is made up of general loss reserves, undisclosed reserves, and subordinated term debt. In practice, the Tier-2 capital of U.S. commercial banks consists primarily of loan loss reserves (see Ng and Roychowdhury, 2014). The sum of Tier 1 and Tier 2 is called "Total Risk-based Capital." Empirically, the impact of these adjustments is quite minor: for example, the correlation between US banks' Tier 1 capital and their reported book equity is 0.995. The correlation between Total Risk-based Capital (Tier 1 + Tier 2) and book equity is 0.982.

[3] A significant literature in accounting deals with earnings and capital management by banks using their provision for loan losses (for example, Beatty et al. 2002, 2014; Shrieves and Dahl et al. 2003). This literature is only tangentially related to our current task – i.e., evaluating the adequacy of banks' equity capital. This is because the main focus in the accounting literature is on the veracity of (and incentive for) each *periodic* loss provision, and its effect on corporate earnings. In our setting, the numerator of the CAR ratio represents the *cumulative* effect of past provisions rather than the impact that *yearly* provisions have on earnings and capital. Furthermore, in the post-BASEL era, financial regulators have always required loan loss allowances to be eliminate from the calculation of Tier 1 capital.

mortgages (50%), and other corporate receivables (100%). Subsequent changes (i.e., Basel II and Basel III) mandated more granular groupings and allowed some large, or internationally active, banks to use their own internal rating-based (IRB) method to compute category risk. But the overall approach of assigning bank's assets into pre-specified risk categories has remained essentially the same under the three Basel pronouncements.

The RWA approach to measuring a bank's risk exposure has been criticized on multiple grounds. For example, the static risk weights in Basel I were broadly viewed as too rigid and too insensitive to changing macro conditions (Engle 2009; Glasserman and Kang 2014). While modifications introduced in Basel II and III allowed for more flexibility, new problems began to surface. In particular, it was noted that banks' own internal rating based (IRB) models produced consistently lower RWAs than prior methods. These IRB methods have been criticized for being too complex, too opaque, too easily manipulated, and too inconsistently applied across banks (Haldane 2012; Le Lesle and Avramova 2012; Basel Committee on Banking Supervision 2013a,b; European Banking Authority 2013; and Mariathasan and Merrouche 2014). In the wake of the global financial crisis, IRB-based methods have also been blamed for introducing an additional source of procyclicality into the banking sector (Andersen 2011; Repullo and Suarez 2012; Behn et al. 2016).[4]

Furthering these concerns, academic evidence suggests that the RWA metrics derived under Basel guidelines do not in fact perform well in capturing the riskiness of banks. For example, RWA corresponds poorly to market-based risk measures, such as stock return volatility (Cordell and King 1995; Das and Sy 2012; and Vallascas and Hagendorff 2013), particularly during periods of market stress (Acharya et al. 2014). Several studies find RWA-based capital adequacy ratios actually underperform simpler CAR constructs that use non-risk-weighted

[4] Under the IRB approach, an asset's risk weight is based on estimates of four parameters: probability of default (PD); loss given default (LGD); exposure at default (EAD); and maturity (M). The higher the estimate for any of these parameters, the higher the risk weight attributed to the loan. PDs are likely to increase during an economic downturn, implying higher capital charges (Behn et al., 2016; Kashyap and Stein, 2004). To the extent that it is difficult or costly for a bank to raise fresh external capital in bad times, it will be forced to cut back on its lending activity, thereby contributing to a worsening of the initial downturn.

denominators, such as total assets (Mayes and Stremmel 2012; Acharya et al. 2014; and Hogan 2015).

In this study, we develop and empirically evaluate a new measure of bank risk. Our approach begins with the observation that a bank's primary source of risk comes from its loan portfolio. Appendix III shows that, irrespective of size, a commercial bank's balance sheet is invariably dominated by its loan portfolio. In a typical commercial bank, the loan portfolio constitutes roughly two-thirds of its total assets, and a much larger proportion of its risk exposure. Yet despite the loan portfolio's importance, the current RWA framework does not employ a portfolio-based approach when evaluating the riskiness of banks.

In this study, we develop a portfolio-level measure of each bank's exposure to default risk, which we dub its *Loan Portfolio Risk* (*LPR*). Our central premise is that the current RWA calculations are fundamentally flawed because they overlook two important economic drivers of bank failures. First, RWA calculations fail to properly account for the intertemporal volatility (or second moment) of the default losses from a bank's loan portfolio over time. Current methods focus sharply on the *average* default rates in each loan category. However, portfolio theory argues that it is the *variance* of these default rates over time that gives rise to the need for higher levels of capital coverage.

Second, the current guidelines fail to adequately address the contagious nature of loan defaults, particularly during a market downturn. An important feature of current RWA calculations is that they are "Property-Portfolio Invariant." Under current Basel guidelines, the riskiness of a property is invariant with respect to the other holdings in the portfolio. As a result, the current RWA calculations fail to account for the risk exposure a bank incurs due to the degree of property concentration in its overall loan portfolio. Clearly the riskiness of a loan portfolio is a function of its exposure to each loan category, as well as the degree to which incidences of default are correlated across loan categories.

We address these problems by extracting loan category information from banks' quarterly Call Reports.[5] Using information from these reports, we decompose each bank's loan portfolio holdings into 14 "loan asset categories." The riskiness of the bank portfolio as a whole is a function of its exposure to each asset category, as well as the variance and cross-correlation structure in the delinquency rates across the 14 loan categories.

Specifically, we measure of the riskiness of a bank's loan portfolio as follows:

$$LPR = \sqrt{\theta \times \Omega \times \theta^T} \quad , \qquad (2)$$

Where: *LPR* refers to a bank's *Loan Portfolio Risk*;

θ is a 1x14 vector of the bank's monetary holdings in each of the 14 loan categories, and θ^T is its transpose;

Ω is a 14x14 Variance-Covariance matrix of the delinquency ratios (DRs) across the different loan types. Each cell in this matrix represents the pairwise covariance between two categories in terms of their delinquency ratios, with the variances for individual loan types populating the diagonal. For this purpose, the delinquency ratio (DR) of a loan category is defined as the ratio of its non-performing loans (NPL) to its total loans outstanding.

Intuitively, *LPR* is the expected dollar losses for the loan portfolio as a whole from a one standard deviation move in historical default rates, taking into account all default cross-correlations.[6] Banks whose loan portfolios are concentrated in

[5] Each FDIC-insured institution is required to file a quarterly Consolidated Reports of Condition and Income (generally referred to as "Call Reports"). These reports provide data on each institution's financial condition and the results of its operations in the form of a balance sheet, an income statement, and a series of supporting schedules.

[6] To illustrate, consider a bank that holds only two types of loans in dollar amount of L_1 and L_2. Let the vector of quarterly historical default ratios for loan types 1 and 2 be represented by DR_1 and DR_2, respectively. Notationally, σ_1 is the standard deviation of DR_1; σ_2 is the standard deviation of DR_2; and σ_{12} is the covariance between DR_1 and DR_2. In this setting, we can write the square of the *Loan Portfolio Risk* variable (LPR^2) as follows:

asset categories with highly volatile delinquency rates will have higher *LPR* scores, particularly if the delinquency rates across these categories exhibit strong positive co-movement over time. Conversely, banks whose holdings are in loan categories with low delinquency rate volatility will have lower *LPR* scores, particularly if the delinquency rates across these categories exhibit low co-movement over time.

Our approach is novel in two important ways. First, our measure focuses on the *variance* (i.e. the second moment) of the historical default rates for each loan category over time, while the current approach focuses on *average* default rates. This distinction is important because the average default rate for each loan type is typically well integrated into existing regulatory metrics, while the volatility of these default rates (a key measure of portfolio risk) have largely eluded capture. Second, our approach takes into account the historical cross-correlation structure for these default rates across loan categories. Thus, *LPR* incorporates information about the default risk of each loan category, as well as the contagious nature of these defaults across time and over different macroeconomic conditions. Prior literature on bank risk recognizes the contagious nature of delinquencies across different loan types, but provide no concrete solutions. We develop a relatively straightforward method that captures this risk at the loan portfolio level.[7]

$$LPR^2 = (L_1, \quad L_2) \times \begin{pmatrix} \sigma_1^2 & \sigma_{12} \\ \sigma_{12} & \sigma_2^2 \end{pmatrix} \times \begin{pmatrix} L_1 \\ L_2 \end{pmatrix} = (L_1\sigma_1^2 + L_2\sigma_{12}, \quad L_1\sigma_{12} + L_2\sigma_2^2) \times \begin{pmatrix} L_1 \\ L_2 \end{pmatrix}$$

$$= (L_1\sigma_1^2 + L_2\sigma_{12}) \times L_1 \; + \; (L_1\sigma_{12} + L_2\sigma_2^2) \times L_2$$

$$= L_1^2\sigma_1^2 + 2\, L_1 L_2\, \sigma_{12} + L_2^2\sigma_2^2$$

Note that LPR^2 is increasing in ${\sigma_1}^2$ and ${\sigma_2}^2$ (the variances of DR_1 and DR_2 respectively) as well as σ_{12} (the covariance between DR_1 and DR_2). Intuitively, LPR^2 measures the time-series variance of the dollar default losses for the entire loan portfolio. Correspondingly, *LPR* is the time-series standard deviation of the expected dollar losses from loan defaults for the entire loan portfolio.

[7] Amiram, Kalay, Sadka (2017) also highlight the importance of industry-level diversification to banks. Specifically, they find lenders demand higher compensation to bear industry-level risk, particularly when loan portfolios are less diversified or during periods when diversification is difficult.

We then propose a new capital adequacy measure that compares a bank's adjusted book equity to its loan portfolio risk (*LPR*), which we refer to as the ***Equity-to-Loan-Portfolio-Risk*** ratio, or *ELPR*:[8]

$$ELPR = ln\left(\frac{book\ equity - intangible\ assets}{LPR}\right) \tag{3}$$

By accounting for the variability of the portfolio's default risk over time, this measure addresses a fundamental weakness of the current regulatory approach to bank risk assessment (promulgated in Basel I through Basel III). A financial institution's capital adequacy ratio, we argue, is better measured as the ratio of its capital base to a standardized measure of its exposure to delinquency risk over time.[9]

Our central hypothesis is that *ELPR* provides a better measure of banks' capital adequacy than existing regulatory alternatives. We test this hypothesis in three ways. In our first set of tests, we examine the usefulness of *ELPR* in predicting bank failures. If *ELPR* is a good ex ante measure of capital adequacy, we would expect low *ELPR* banks to fail more frequently than high *ELPR* banks. As a benchmark, we compare the predictive power of *ELPR* to that of a common regulatory measure of capital adequacy, *T1CR*, defined as a bank's Tier-1 Capital divided by its RWA. All these tests are out-of-sample, in the sense that we use historical data available at each point in time to predict future bank failures. We do not do any in-sample fitting when constructing the prediction indicators.

[8] We deduct intangible assets from book equity in the numerator because it is a common adjustment when regulators compute Tier-1 (or Core) capital for banks. Empirically, this adjustment makes little difference to our results. We also replaced book equity with banks' actual Tier-1 capital, and again the results remain substantively unchanged.

[9] As an alternative formulation, we can also deduct the expected loss from default from the numerator when computing *ELPR*. For this purpose, expected loss would be defined as the linear sum of current holdings in each loan category, multiplied by its historical default rate. Note that if each bank has already accrued for expected loan losses based on prior default rates, this adjustment would be redundant, as their reported book equity would already be net of mean expected losses. This is in fact what we find, as the adjustment made no material difference to our results. We thus use the simpler formulation.

Our results show *ELPR* dominates *T1CR* in bank failure predictions. Over one-year horizons, the Pseudo-R^2 from a Logit failure prediction model using *T1CR* alone is 17.1%, while it is 24.7% using *ELPR* alone. Further, as the forecast horizon increases, the advantage of *ELPR* over *T1CR* becomes increasingly more dramatic. In two-year-ahead predictions, *ELPR* has a Pseudo-R^2 of 17.3%, compared to 5.5% for *T1CR*. In five-year-ahead predictions, *T1CR* is essentially useless (Pseudo-R^2 = 0.7%) while *ELPR* retains significant predictive power (Pseudo-R^2 = 7.7%). Using receiver operating characteristic (ROC) curves and other prediction analytics, we show that this main finding is robust to a range of perturbations in the test parameters (Demers, and Joos, 2007; Jones, 2017) and relative misclassification cost assumptions (Martin, 1977; Sinkey, 1975). This result also remains strikingly clear when we predict bank failures using a hazard-type model (Shumway, 2001), and when we separately evaluate subpopulations of large, small, and medium sized banks (Berger and Bouwman, 2013).

Our second set of tests examine the increment usefulness of *ELPR* in bank failure predictions after controlling for a host of other regulatory indicators of bank health. The set of metrics commonly used by regulators to monitor banks' financial health is often referred to collectively as the "CAMELS" indicators. This acronym refers to: C – Capital Adequacy; A – Asset Quality; M – Management Efficiency; E- Earnings; and L – Liquidity; and S – Sensitivity to Interest Rates (see Appendix V for details on how each variable is constructed). If the information about a bank's structural risk contained in *ELPR* is already captured by other regulatory metrics, we would not expect it to be incrementally useful in bank failure prediction after controlling for CAMELS indicators.

Our results show that not only does *ELPR* dominate each component of CAMELS individually, it is also strikingly additive when all the CAMELS variables are included in the model. Furthermore, the usefulness of *ELPR* increases sharply as we increase the forecast horizon. In one-year-ahead forecasts, *ELPR* adds significantly to the CAMELS variables. In two- through five-year-ahead forecasts, *ELPR*, as a standalone variable, actually has higher predictive power for bank failures than the entire set of CAMELS variables. Again, the robustness of this result is validated across a wide range of parameters using ROC curves and misclassification cost tests, and holds for subpopulations of small, medium, and large banks.

Overall, our first two sets of results show *ELPR* captures a low-frequency form of failure risk, which becomes increasingly obvious with time. This is consistent with the economic intuition behind our calculation of *LPR:* that is, the capital adequacy of a bank should be assessed by comparing its equity to the likely range (and magnitude) of default losses over time across its entire portfolio. Our results show that *ELPR* captures important cross-sectional differences in banks' likelihood of failure up to five years in advance, even controlling for the full suite of CAMELS variables.

In our third set of tests, we examine the implications of *ELPR* for the stock prices of bank holding companies. Specifically, we are interested in understanding the extent to which public equity pricing of bank holding companies reflects the riskiness of banks as captured by *ELPR.* Of the 10,995 unique banks in our sample, 2,030 (18.46%) were held by publicly-listed bank holding companies. Each of these publicly-listed companies controls one or more commercial banks. Using textual analysis methods, we trace the ownership information in banks' quarterly Call Reports to its top-level bank holding company. Matching these holding companies to the CRSP database, we were able to assemble a sample of 791 unique publicly-listed bank holding companies that controlled at least one commercial bank during our sample period.

We use this sample of publicly-traded firms to address two empirical questions: (a) is the latent risk captured by *ELPR* reflected in the implied cost-of-capital (ICC) of these bank holding companies, and (b) is *ELPR* useful in predicting the future stock returns of these companies. The first question is focused on market awareness: do equity investors demand a higher average rate of return from firms with lower *ELPRs* (i.e. do lower *ELPR* firms have higher average "price implied discount rates").[10] If equity investors are aware of, and price in, the high bank

[10] A firm's market implied cost of capital (ICC) is the internal rate of return that equates the present value of its expected cash flows to its current stock price. Assuming we can reasonably estimate a firm's expected cash flows, its ICC is simply the interest rate that the market is implicitly using

failure risk associated with low *ELPR* firms, we would expect low *ELPR* firms to have higher average implied cost-of-capital (ICC) measures, after controlling for other determinants of ICCs.

The second question is focused on market pricing efficiency: that is, whether the prices of bank holding companies *fully and efficiently* reflect the implications of *ELPR* for future stock returns. Under the null of fully efficient pricing, low *ELPR* firms are "riskier" and should earn higher average returns; conversely, if equity investors do not fully appreciate the riskier nature of low *ELPR* firms, they may overpay for these companies. Under this alternative mispricing hypothesis, low *ELPR* firms (i.e. less adequately capitalized firms) may in fact earn lower returns, particularly during economic downturns, when their risk exposure is most likely to become transparent.

Our ICC results show that equity markets are aware of the risk associated with *ELPR.* For our full-sample period (2002-2016), the most capital adequate (top *ELPR* decile) firms have an average ICC that is 1.9% to 2.4% lower than the least capital adequate (bottom *ELPR* decile) firms, after controlling for other known determinants of ICCs. Historically, equity costs-of-capital in the United States have ranged from 8% to 12%, so this spread between high and low *ELPR* firms is quite economically important. Interestingly, the ICC difference associated with *ELPR* is only 1.4% to 1.7% during non-crisis periods. During the financial crisis (2007-2010), this difference in ICC more than doubles, to 3.6% to 4.8% per year. Evidently equity market participants were much more aware of banks' capital adequacy risk during the crisis, and demanded a higher risk premium from low *ELPR* firms during these years.

Finally, our returns prediction tests for bank holding companies show that *ELPR* is on average *positively* correlated with the future returns of these companies.

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to discount these cash flows. ICCs are commonly estimated by equating the expected cash flows of each firm to its current stock price, and imputing the implied discount rate. An extensive literature in accounting discusses methodological issues in ICC construction (see Lee, So, and Wang, 2017, for a summary of this literature). In this study, we combine a simple mechanical earnings forecasting model with a residual income valuation model to derive our ICC estimates (see Section 5 for details).

Over the entire sample period, top-decile *ELPR* firms earn 6.93% higher average annualized returns than bottom-decile *ELPR* firms (t-statistic 4.04). Further, we find that this difference in returns is driven entirely by the global financial crisis period. In the months surrounding the global financial crisis (7/2007-6/2011) top-decile *ELPR* firms earned a remarkable 40.21% higher average annualized returns than bottom-decile *ELPR* firms (t-statistic 12.2). This abnormal return is still an extraordinary 3.33% per month after controlling for all five Fama-French factors (Fama and French, 2015).

These findings are consistent with market mispricing, and more difficult to reconcile with risk-based explanations. Our earlier results suggest that higher *ELPR* firms are "safer" (i.e. they are less prone to failure) than low *ELPR* firms. Thus rational pricing predicts *lower* average returns for high *ELPR* firms. This is not what we observe, as the safer high *ELPR* firms earn higher average returns. Further, contrary to the predictions of rational pricing but consistent with the mispricing hypothesis, low *ELPR* firms dramatically underperform during a financial crisis. On balance, these findings support the notion that the latent risk in low *ELPR* firms is not fully priced in by the market.

Our results contribute to academic and regulatory debates on the design of capital adequacy metrics for commercial banks. A number of studies have raised concerns about the inability of regulatory risk-weights to reflect the economic risk faced by commercial banks (Engle 2009; Glasserman and Kang 2014). Attempts to mitigate this problem by allowing banks greater flexibility through the internal rating-based (IRB) models have also been criticized for their opacity, and subjectivity (Haldane 2012, LeLesle and Avramova 2012, Basel Committee on Banking Supervision 2013a,b, European Banking Authority 2013, and Mariathasan and Merrouche 2014), as well as their procyclical tendencies (Andersen 2011; Behn et al. 2016; Kashyap and Stein 2004).

Our evidence suggests that a variable based on portfolio-level default volatility, such as *ELPR,* can provide a more satisfying solution. Unlike static risk weights, *ELPR* captures intertemporal variations in default risk over business cycles. Further, because *ELPR* is based on the long-run variance of delinquency rates rather than recent quarterly estimates, it should significantly mitigate procyclicality concerns associated with IRB-based estimates. Unlike most IRBs, our approach does not require on bank-specific inputs beyond what is already disclosed in their quarterly filings. Therefore this approach is more transparent and objective than existing IRB methods to risk-weight estimation. In terms of both conceptual appeal and empirical performance, *ELPR* seems to dominate capital adequacy measures commonly used by regulators.

Our results also extends the literature on bank failure predictions. An early literature extending back to the 1970s attempted to identify ex ante predictors of bank failures using accounting data (Meyer and Pifer 1970; Sinkey 1975, 1977; and Martin 1977). Most of the factors discussed in this literature are now integrated into the CAMELS monitoring system.[11] While these studies have added to our understanding of bank failure predictability, a recurrent concern is the tendency of CAMELS indicators to deteriorate quickly – i.e., their predictive power for bank failure becomes quite weak by the second or third quarter after rating assignment (Cole and Gunther 1998). We contribute to this literature by demonstrating that *ELPR* is additive to CAMELS variables, and it is able to capture considerable cross-sectional variation in bank failure rates up to five years prior to the event.

Overall, our results nominate *ELPR* as an attractive, and likely superior, approach to measuring the riskiness of commercial banks. One caveat to our empirical analysis is that it is based on a relatively short sample period. Our data spans around 15 years (1/2003 to 12/2017 for bank failure prediction; 7/2002 to 6/2017 for return forecasting). It remains to be seen whether these results are generalizable to other, longer, time periods. That said, we believe the conceptual appeal of our approach is intuitive, and the empirical evidence to date shows substantial promise.

[11] Other studies have looked to external sources, such the stock market and credit rating agencies, for additional input in bank failure prediction (Pettway and Sinkey 1980; Bongini 2002). Still other studies link the likelihood of a bank failure to the regulatory proclivity towards forbearance (Brown and Dinc, 2005, 2011) as well as other firm attributes, as ownership structure (Berger et al. 2016) and inter-bank competition (Akins et al. 2016).

2. Data

We obtain a sample of bank failures from the FDIC "Failed Institutions List" as reported by the FDIC.[12] This list provides details about each FDIC-insured commercial bank or thrift company (hereafter, bank), that failed or entered FDIC conservatorship. For each failed bank, this database provides: the bank name, its location, the effective date of the failure (i.e., the date that failed bank enter into FDIC conservatorship), total assets and deposits as of the last Call Report prior to the effective date, the estimated cost of the failure to the FDIC, as well as information on the acquiring institution (if applicable).[13] This list reports 538 bank failures from 2003 through 2017.

Next, we obtain quarterly financial data on individual banks from the FDIC SDI data repository (link). This repository contains information assembled by the FDIC from the Consolidated Reports of Condition and Income (generally referred to as "Call Reports") that each FDIC-insured institution is required to file quarterly. These reports provide quarterly data on each institution's financial condition and the results of its operations in the form of a balance sheet, an income statement, and a series of supporting schedules. For recognition and measurement purposes, the Call Reports generally conform to US generally accepted accounting principles (GAAP). However, because each Call Report is a bank-level document, each individual bank (together with its consolidated subsidiaries) is considered separate reporting entity.[14]

Our approach calls for the estimation of a variance-covariance matrix of the default rates in each of the 14 loan categories. We compute this matrix using quarterly loan delinquency data extracted from the FDIC Quarterly Banking Profile (QBP) document. This quarterly report contains the total amount of non-performing loans and leases by various loan categories for all FDIC-insured

[12] https://www.fdic.gov/bank/individual/failed/banklist.html

[13] The cost of a bank failure is computed by the FDIC following a clear formula. Essentially, it is the net cost to the FDIC of the bailout after an orderly dissolution of the bank assets.

[14] Each Call Report is reviewed by the FDIC for errors or omissions using a variety of audit flags, but is typically not audited by an independent external auditor. For private institutions, the Call Report is the only publicly-available source of financial information. Therefore, our sample is limited to variables that can be constructed based on these reports.

institutions. For each loan category, the report breaks down: (a) amounts past due 30-89 days and still accruing interest, (b) 90 or more days past due and still accruing interest; and (c) overdue loans on which interest is no longer being accrued. We define the delinquency ratio (DR) for each loan category as the sum of these three numbers, divided by the total loan outstanding in that category. The individual entries in the matrix represent pairwise covariances of the DRs across the fourteen loan categories, with the variances for individual loan types populating the diagonal.[15]

We use the FDIC QBP data from its first availability (first quarter of 1991) to the end of 2001 to estimate our initial covariance matrix. This ensures our calculation makes use of at least 43 quarters of prior data. In subsequent years, we estimate the matrix using an expanding window that includes data starting from Q1 1991 through to the most recent calendar year that ended at least 12 months before year of interest. This procedure ensures we do not have a "peek ahead" bias when predicting future bank failures. We test our predictions on bank failures that occurred during the period 2003-2017.

3. Institutional Background and Descriptive Statistics

3.1 The Importance of Loan Portfolios to Banks

The core operation of a commercial bank involves taking in funds from depositors and lending these funds out to individuals and businesses. As a result, the most important asset on its balance sheet is its loan portfolio. Although banks prefer to make loans as their primary business, excess liquidity is also invested into other debt securities, such as Agency MBSs, US Treasury securities, US Government obligations, securities issued by states & political subdivisions, other domestic

[15] We use the delinquency data from FDIC QBP documents rather than summing up the loan default data from individual banks because, prior to March 31, 2001, the quarterly reports on individual banks did not include information on loans that are 30 to 89 days past due. Although regulators have consistently found 30-89 day past due information helpful in identifying potential problem banks, prior to 2001, this information was deemed too sensitive and confidential to be included in FDIC quarterly reports on individual banks. Because we only need the quarterly aggregated delinquency ratio for each loan category to construct the variance-covariance matrix, the QBP document offers us a longer time series.

debt securities, and foreign debt securities. Among them, US Government obligations make up the vast majority.

In Appendix III, we present summary statistics on the importance of the loan portfolios and debt securities to U.S banks over our sample period (2001 to 2015). To construct this table, we sort all banks into ten size deciles based on end-of-year total asset. Decile 1 (10) represents the largest (smallest) banks. For each size decile, we report the mean and median loan portfolio and debt securities, each expressed as a percentage of total assets. This table shows that loan portfolios represent roughly 55 to 70 percent of banks' total assets. The loan portfolio is the most important asset, irrespective of bank size. Debt securities, as the second largest component of assets, usually constitute around 20% of total assets. Clearly banks' loan portfolios are crucial, both as a driver of expected returns and as a source of risk. When loans go bad, banks fail, especially during an economic downturn. Our analysis therefore focuses on the delinquency risk of banks' loan portfolios.[16]

3.2 Bank Loan Portfolio Composition

Appendix IV presents descriptive statistics on banks' loan portfolios. Our sample consists of 111,453 firm-years from 2001 to 2015. Using FDIC's loan classifications as a starting point, we divide bank loans into 14 different categories[17]. We present summary statistics for each loan category, arranged in descending order according to their relative importance in the aggregate portfolio. Columns 1 and 2 report Aggregate Level statistics, whereby outstanding loans are summed across all banks before averages are computed. Column 1 reports the

[16] Adding debt securities to the loan portfolio when constructing *ELPR* yields no significant improvement in terms of failure prediction or return forecasting.

[17] The FDIC Quarterly Banking Profile divides total loan and leases into 9 categories: 1) Total real estate loans; 2) Loans to depository institutions; 3) Agricultural production loans; 4) Commercial & industrial loans; 5) Credit cards; 6) Other loans to individuals; 7) Loans to foreign governments and official institutions; 8) All other loans; 9) Lease financing receivables. Among these categories, real estate loans are by far the largest category, accounting for over 50% of the aggregate loan portfolio. To improve granularity, we further divide real estate loans into six groups based on information provided by the FDIC Quarterly Banking Profile: 1) Construction and development loans; 2) Real estate loans secured by farmland; 3) Real estate loans secured by 1-4 family residential properties; 4) Real estate loans secured by multifamily residential properties; 5) Real estate loans secured by nonfarm nonresidential properties; 6) Real estate loans in foreign offices.

percentage share of the aggregate loan portfolio represented by each loan type (Ratio). Column 2 reports the aggregate non-performing loan (NPL) in each loan category. Columns 3-8 report bank-level results. Specifically, table values in Column 3 are the loan type percentage when variables are first computed at the bank-level and then averaged across all banks. Columns 4-8 report descriptive bank-level statistics for each loan type, in millions of dollars.

The most important loan category is Real Estate loans secured by 1-4 family residential properties (RES), constituting 33.90% of total loans. Commercial and industrial loans (C&I) comes in a distant second at 18.67%. Real estate loans secured by nonfarm nonresidential properties (NRES) account for 13.32%, and other consumer loans (CONOTH) make up 8.73%, followed by credit card loans (CRCD) at 6.96%, and construction and development loans (CONSTRUCTION) at around 5%. All other loans types are less than 5%. Construction and development loans (CONSTRUCTION) had the highest delinquency rate during our sample period, with an average non-performing loan ratio of 6.19%. The second riskiest loans are residential real estate loans (RES), with a default rate of 5.43%. In contrast, loans to depository institutions (INSTITUTION) had the lowest delinquency ratio, at only 0.13%. Columns 4 to 8 report bank-level descriptive statistics for each loan type, in millions of dollars. These statistics show the wide variation in loan composition across banks. Coupled with the wide variation in NPL ratios across loan types, this evidence suggests loan portfolio composition can be an important driver of bank risk.

3.3 Correlation in Delinquency Rates and Variance-covariance Matrix

Panel A of Table 2 presents the Pearson Correlations for quarterly NPL ratios across different loan categories from 1991Q1 to 2015Q4. To construct this table, we compute aggregate non-performing loan (NPL) ratios for each loan category at the banking industry level. Specifically, an NPL ratio is defined as the aggregate non-performing loans divided by aggregate total loans, for that industry and quarter.[18] Correlation coefficients above 0.5 are presented in bold italic.

[18] We compute aggregate NPL ratios at the industry-level because bank-level or state-level NPL data is not always available. First, loan amounts past due 30-89 days for individual bank were

The pairwise correlations in delinquency rates across loan categories are broadly positive, indicating a significant contagion effect. Nearly 65% (59 out of 91) of the pairwise correlations are above 0.5; and only 7 are negative. Figure 1 presents time-series graphs of the quarterly aggregate NPL ratios for each loan type. Clearly delinquency rates across the 14 categories tend to move up or down together over the time. However, at any given point in time, these ratios vary significantly in the cross-section.[19]

Panel B of Table 2 reports the variance-covariance matrix of aggregate delinquency rates across different loan types for the corresponding period. The variances for individual loan types populate the diagonal, indicating the volatility of default rate. Other cells in the matrix represent pairwise covariance terms across different loan categories in terms of their quarterly delinquency ratios. Higher value indicates greater joint variability between two loan types over time. Note that this panel can be used, in conjunction with each bank's quarterly call report, to produce a measure of its current quarter *ELPR.*

3.4 Bank Failures in the U.S.

A bank failure is the closing of a bank by a federal or state banking regulatory agency. Typically, a bank is closed when it becomes critically undercapitalized or is unable to meet its obligations to depositors and others. This determination is made by the bank's appropriate Federal banking agency (usually the FDIC; the Board of Governors of the Federal Reserve System; or the Office of the Controller of the Currency, aka OCC). In the event of a failure, the FDIC has two

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not publicly available until 2001, so we can't calculate the bank-level NPL ratio. Second, some states (such as Alaska) have only a small number of banking institutions, so state-level loan exposures may be unreliable. Finally, not all banks supply a breakdown for every loan type each quarter, which can lead to omissions in NPL calculation. To ensure the variance-covariance matrix can be calculated for a sufficiently long time-series, industry-level aggregation turned out to be the most practical solution.

[19] Prior studies that examine loan composition (Liu and Ryan 1995; Bhat, Lee and Ryan 2019; Harris, Khan and Nissim 2018) generally emphasize differences in *mean* default rates across loan types, rather than the *variance* and *covariance* of these default rates. Our analysis suggests both concentration in high variance loans and default rate correlation across loan types, can convey meaningful information about the riskiness of a loan portfolio risk.

responsibilities. First, as the insurer of the bank's deposits, the FDIC pays insurance to the depositors up to the insured limit. Second, as the receiver of failed banks, the FDIC assumes responsibility for the orderly disposal of bank assets and the settling of its debts, including claims for deposits in excess of the insured limit.

Table 1 provides descriptive statistics for U.S. bank failures between 2003 and 2017. Column 1 reports the number of FDIC insured banks and thrifts (including savings and loans associations and saving banks) at the beginning of each year. Column 2 reports the number of bank failures that occurred during the year. Column 3 reports failures as a percentage of banks that existed at the beginning of the year. Column 4 reports the estimated loss arising from these failures.[20]

As Table 1 shows, banks failures are not rare events in the United States. Furthermore, these failures tend to be clustered over time, increasing sharply after the collapse of Lehman Brothers (September 15, 2008). The failure rate remained high in the 2009-2012 period, only tapering off gradually in the subsequent years. Most recently, there were 5 failures in 2016 and 8 failures in 2017. Figure 2 provides a graphic depiction of these results.

The data on estimated losses show that bank failures can exert significant pressure on the FDIC insurance fund. For example, the estimated cost to FDIC was $18.16 billion in 2008, $26.96 billion in 2009 and $16.36 billion in 2010. As bank failures rise, the DIF fell to the lowest point in its history by year-end 2009: a negative $20.9 billion on an accounting basis.[21] In aggregate the 538 bank failures during our sample period resulted in an estimated cost of $74.47 billion to the FDIC.

[20] This estimated loss is obtained from the FDIC Failed Institutions report, and represents the difference between the amount disbursed from the Deposit Insurance Fund (DIF) to cover obligations and the amount recoverable from the liquidation of the receivership estate. In ongoing cases, these losses are based on estimates, which are routinely adjusted with updated information from new appraisals and asset sales. The estimated loss reported in Table 1 are as of December 31, 2017.

[21] https://www.fdic.gov/bank/historical/crisis/overview.pdf

4. Bank Failure Predictions

In this section we evaluate the usefulness of *ELPR* and other classifiers in predicting bank failures. Consistent with prior literature (e.g., Ng and Roychowdhury 2014), our main tests are based on a logistic regression model:[22]

$$FAIL_{i,t} = \beta_h X_{i,t-h} + \varepsilon_{i,h} \, , \quad where \ h = 2, \ldots, 6 \qquad (4)$$

The dependent variable, $FAIL_{i,t}$, is an indicator variable: set equal to 1 when bank *i* is identified as having failed during year *t*; it is set equal to 0 if bank *i* survives the year. Only banks that are operational at the beginning of year *t* are included. Banks that have already failed, or banks that ceased to exist due a merger or an acquisition, are excluded.

We evaluate the predictive performance of the model at a various time horizons, ranging from 1- to 5-years (*h* = 2,…,6) prior to the year of interest. We use *h*=2 to designate the one-year-ahead forecast because the financial data used for this forecast comes from fiscal year ended December 31, *t-2.*[23] In this equation, $X_{i,t-h}$ is a vector of predictor variables for bank *i*, as reported on December 31st in *t-h* year, where *h* equals 2,…,6. β_h is a vector of regression coefficients for explanatory variables at the end of year *t-h*. $\varepsilon_{i,h}$ is the error term. We cluster standard errors at the bank level to account for the lack of independence between bank-year observations (Petersen 2009).

4.1 ELPR versus T1CR

We begin by empirically evaluating the predictive power of *ELPR* relative to that of a commonly used regulatory capital adequacy ratio (*T1CR*). *T1CR* is defined

[22] We use Logit as its assumption of fatter-tailed error distributions corresponds better to the frequency of bank failure events (e.g., Van den Berg, Candelon and Urbain, 2008). Our robustness tests show the main results all hold when a Hazard model (Shumway 2001) is used instead.

[23] This procedure ensures all data used in our model are publicly available at the time of the forecast. For example, First Commercial Bank of Florida closed down on January 07, 2011, which is only seven days after fiscal year ended 2010. By imposing an *h=2* requirement, our one-year-ahead forecasting model will use data from fiscal year ended December 31, 2009, thus ensuring no peek-ahead bias.

as a bank's Tier 1 capital divided by its risk-weighted-asset (RWA). The inputs for this calculation are extracted from each bank's quarterly Call Report. *T1CR* is the first component of the CAMELS indicators. Conceptually, it is also closest in spirit to the *ELPR* variable developed in this paper.[24] We evaluate the performance of these predictor variables using three traditional metrics: Pseudo-R^2 (also known as McFadden's LRI); the area under Receiver Operating Characteristic (ROC) curves; and misclassification cost.

Table 3 presents the results of logistic regression models with different prediction horizons. Panel A results show that in one-year-ahead forecasts, both *ELPR* and *T1CR* exhibit excellent predictive power, with pseudo-R^2s of 24.7% and 17.1%, respectively. The combined model achieves a pseudo-R^2 of 25.5%, indicating *ELPR* provides additive information about future failures in the presence of *T1CR*. When the forecast horizon is extended, the superiority of *ELPR* over *T1CR* is even more noticeable. In two-year-ahead forecasts, the pseudo-R^2 for *T1CR* falls to 5.5% while the pseudo-R^2 of *ELPR* remains quite high at 17.3%. With even longer forecast horizons, *T1CR*'s usefulness plummets (pseudo-R^2s of 1.5%, 0.9%, and 0.7%, in the 3-, 4-, and 5-year horizons respectively), while the *ELPR* continues to exhibit reliable predictive power (pseudo-R^2 s of 12.8%, 9.8% and 7.7%, in the 3- to 5-year horizons, respectively). Overall, Table 3 results show *ELPR* is superior to *T1CR* over every forecast horizon, with the difference being especially clear in longer horizons.

A Receiver Operating Characteristics (ROC) curve provides a concise graphic representation of the diagnostic ability of different model over alternative threshold cut-off values (e.g., Demers and Joos 2007; Jones 2017). Specifically, these graphs plot a model's Sensitivity against {one minus its Specificity}; where Sensitivity is the fraction of observed positive outcomes that are correctly classified (i.e., it is one minus the type I error), and Specificity is the fraction of observed negative outcomes that are correctly classified (i.e., one minus the type

[24] If, instead of *T1CR*, we benchmarked *ELPR* against other variations of the regulatory capital adequacy ratio, such as total risk-based capital ratio, the main results would remain virtually unchanged. Some prior studies (e.g., Meiselman, Nagel, and Purnanandam 2018) also used *Scaled-RWA* (RWA divided by total assets) as a performance benchmark. We find *Scaled-RWA* performs much weaker than *T1CR* in our tests.

II error). The area under the ROC curve (denoted AUC) ranges from 0 to 1, and provides a summary measure of the discriminative ability of each model. The closer a ROC curve is to the upper left corner, the more efficient is the prediction model. For reference, a perfect classifier has an AUC equal to 1, while a coin toss has an expected AUC of 0.5. We can convert an AUC to an Accuracy Rate (AR) measure, aka a Gini coefficient, by the formula: AR=2×AUC-1.

Figure 3 depicts ROC curves for *ELPR*, *T1CR* and a predictive model that combines both variables. Consistent with Table 3 findings, *ELPR* dominates *T1CR* across all forecast horizons. Further, *ELPR* exhibits incremental usefulness when added to *T1CR* in across all forecast horizons. Specifically, adding *ELPR* to the model increases the accuracy rate by 7.02%, 17.12%, 25.36%, 25.58%, and 24.84%, for 1- through 5-year forecast horizons, respectively.[25] We can also see that the relative advantage of *ELPR* over *T1CR* is much more pronounced for longer horizons.

Evidence that *ELPR* yields superior classification accuracy does not necessarily imply it is superior in terms of misclassification costs. This is because: (a) prior probabilities of a failure are low (i.e., bank failures do not occur frequently), and (b) misclassification costs are typically asymmetric (i.e. costs associated with a false negative are typically much higher than costs associated with false positives). These highly unbalanced prior probabilities and misclassification costs suggest a need to take misclassification costs into account when evaluating the performance of the predictive variables.

In our Online Appendix, we perform extensive misclassification cost analyses using a wide range of relative cost assumptions consistent with prior studies on bank failures predictions (e.g., Frydman et al. 1985; Tam and Kiang 1992). Our results show *ELPR* dominates *T1CR* in every relative cost assumption category.

[25] Take the 1-year forecast horizon as an example. In the *T1CR* model, AUC is 0.8722 and the corresponding accuracy rate is 74.44%. After including *ELPR*, AUC becomes 0.9073 and the accuracy rate is 81.46%. Therefore, the accuracy rate in the combined model represents an increase of 7.02% (81.46%-74.44%) over that of the *T1CR* model.

These results provide additional support for the superiority of *ELPR* over *T1CR* in terms of their ability to predict future bank failures.

4.2 Silver State Bank: A Case Study

In Appendix VI, we provide a case study that illustrates the source of the informational advantage of *ELPR* over *T1CR*. On September 5, 2008, Silver State Bank was closed by the Nevada Financial Institutions Division and control of its assets was handed over to the FDIC as Receiver. The underlying cause of this bank's failure was its overexposure to risky real estate loans, especially mortgages on undeveloped land purchased for home construction. Looking back to financial data reported by the bank at the end of 2006, just before global financial crisis, we show that its *ELPR* places the bank in the lowest percentile by historical distributions as of 31/12/2006. Thus, *ELPR* would have clearly flagged Silver State Bank as being undercapitalized and at high risk of failure by the end of 2006. Note that this analysis was done using only historical NPL ratios and cross-correlation patterns that were publicly available as of 31/12/2006.

Unfortunately, as our analysis shows, the main regulatory metrics used to monitor banks, such as *T1CR* and other CAMELS variables, would have classified the bank as being well capitalized. The *T1CR* variable failed to capture the deteriorating conditions in the commercial real estate and home construction loan categories, and the high correlation in the NPL rates between these two loan types (pairwise correlation of 0.86). The other CAMELS indicators failed to pick up the mounting risk in this bank in part because of their reliance on profitability (the bank was quite profitable in 2006 and 2007). Even as late as year-end 2007, bank regulators still regarded Silver State Bank as well-capitalized. However, the riskiness of its loan portfolio can be detected by *ELPR* as early as 2006.

4.3 ELPR versus CAMELS

In 1979, the Uniform Financial Institutions Rating System (UFIRS), globally known by the abbreviation CAMEL, was introduced by the Federal Financial Institutions Examination Council (FFIEC) in the United States. CAMEL stands for: capital adequacy (C), asset quality (A), management experience (M), earnings (E), and liquidity (L). In 1995, in response to rapid changes in the banking industry, the Federal Reserve and the OCC upgraded the original rating by adding a measure of the bank's sensitivity to market risk (S). The resulting CAMELS rating system is now used by regulators around the world to monitor banks' financial health. To prevent potential bank runs in the event of a large rating downgrade, the actual rating scores are only relayed to the bank's senior management, and not released to the public.

Academic studies that have examined the usefulness of CAMELS indicators in predicting bank failures have, by and large, found that they do contain useful information (e.g., Tam and Kiang 1992; Bongini, Claessens and Ferri 2001; Kerstein and Kozberg 2013; Betz, Oprică, Peltonen and Sarlin 2014). Note that these studies do not have the actual CAMELS scores computed by regulators (which are not released). Instead, academics have developed proxies for each variable in the CAMELS system using publicly available financial data. In this section, we compare the performance of the CAMELS variables to *ELPR*. Following prior literature (e.g., Bushman and Williams 2015; Duchin and Sosyura 2012, 2014; Berger and Roman 2015), we compute a proxy for each CAMELS variable using public data: C (tier 1 capital), A (non-performing loan ratio), M&E (ROA), L (cash/deposits), S (net short-term assets as a percentage of total assets). These variables' constructions are detailed in Appendix V.[26]

Table 4 examines the performance of *ELPR* and CAMELS variables across different forecast horizons. These results focus on Pseudo-R^2 and Accuracy Rates. For the 1-year horizon, the CAMEL system performs quite well (pseudo-R^2 = 33.3%; accuracy rate = 86.00%). However, *ELPR* alone achieves prediction power comparable to the entire CAMELS system (pseudo-R^2 of 24.7% and an

[26] Because regulatory rating scores are confidential, the proxies in appendix V are only approximations designed to capture each of the six dimensions of the CAMELS system. Our construction follows prior academic studies. In particular, we follow Bushman and Williams [2011] in using a bank's ROA to proxy for management quality. This approach is motivated by findings from DeYoung [1998]. Using confidential information on actual CAMELS ratings, DeYoung [1998] shows that regulators' assessment of management quality correlates with multiple bank characteristics, among which ROA is the most important. We also use alternative accounting ratios to proxy for other CAMELS content (for example, measuring capital adequacy as the ratio of book equity to total assets), but found little difference in the results.

accuracy rate of 80.91%). *ELPR* also dominates each of the individual components of CAMELS. After adding *ELPR*, the predictive ability of the CAMELS system increases, with the pseudo-R^2 increasing from 33.3% to 37.5% and the Accuracy Rate from 86.00% to 88.74%. As we move to longer horizons, the predictive capability of the CAMELS system deteriorates quickly (Cole and Gunther (1998) reports a similar finding). In longer horizon predictions, *ELPR* begins to dominate CAMELS. For instance, over a 3-year forecast period, the CAMELS model only achieves a pseudo-R^2 of 6.8% and Accuracy Rate of 54.36%. After adding *ELPR* into the CAMELS framework, the combined model achieves a pseudo-R^2 of 17.1% and an Accuracy Rate of 72.24%. A more detailed misclassification cost analysis, reported in our Online Appendix, further validates the benefits of adding *ELPR* to the suite of *CAMELS* predictors in each relative cost assumption category.

In sum, our results show that *ELPR* dominates each component of CAMELS individually, and is also strikingly additive to the CAMELS indicators when all variables are included in the prediction model. Furthermore, the relative usefulness of *ELPR* increases sharply as the forecast horizon is lengthened.

4.4 Relative Importance of Variance and Covariance Information

Our results thus far show *ELPR* contains important information about future bank failures beyond what is being captured by the CAMELS variables. This information can reflect two (related) types of bank-level risk: (a) Variance risk, whereby high *ELPR* banks are primarily those exposed to categories with highly volatile default rates (i.e. high DR variance loans), and (b) Covariance risk, whereby high *ELPR* banks are primarily those exposed to categories with high covariance over time (i.e. high DR covariance loans). To better understand the source of this informational advantage, we parse *ELPR* into a variance-related and a co-variance related component.

First, for each bank-year observation, we derive a version of *LPR* using only information in the off-diagonal of its variance-covariance matrix of DRs. Specifically, we compute:

$$COVAR = \ln\left(\frac{book\ equity - intangible\ assets}{LPR\_Covariance}\right);$$

where *LPR_Covariance* is estimated from variance-covariance matrix with the variance terms set to zero. We then regress *ELPR* on *COVAR* as follows:

$$ELPR = \alpha + \beta \times COVAR + \varepsilon \qquad (5)$$

The unique information in the variance (*VAR_unq*) is then defined as the residual from estimating equation (5).

Symmetrically, we can allow the variance-related information to have first shot by computing a version of *LPR* using only information in variance terms:

$$VAR = \ln\left(\frac{book\ equity - intangible\ assets}{LPR\_Variance}\right);$$

where *LPR_Variance* is derived from the variance-covariance matrix with the covariance terms set to zero. We can then regress *ELPR* on *VAR* as follows:

$$ELPR = \alpha + \beta \times VAR + \varepsilon \qquad (6)$$

The unique information in covariance (*COV_unq*) can then be defined as the residual from estimating equation (6).[27]

In Table 5, we report the results of a set of logistic regressions of future bank failure on (a) *VAR* and *COV_unq*, and (b) *COVAR* and *VAR_unq*. In each case, we include all the CAMELS variables as controls. In these regressions, the coefficient on *VAR_unq* (*COV_unq*) captures the incremental explanatory power of the variance- (covariance-) related information, after allowing the covariance- (variance-) related information to have a first shot at predicting bank failures.

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[27] Because *LPR_Variance* and *LPR_Covariance* are highly correlated, it's inappropriate to compare the Pseudo-R^2s of *COV* and *COVAR* without orthogonalizing these variables.

Table 5 results show that both variance-related information and covariance-related information provide incremental explanatory power over each other, after controlling for the CAMELS variables. With the exception of the covariance-related information in the 5-year-ahead forecast, this result is robust across all prediction horizons. On a stand-alone basis, the variance-related (*VAR*) information appears to be more important than the covariance-related information (*COVAR*). Taken together, these results indicate that bank-level risk derives from both the high volatility of DRs in individual loan types, as well as strong contagion effects between different loan categories.

5. Implications for the Stock Market

In this section, we examine the implications of *ELPR* for the stock prices of publicly traded bank holding companies (BHCs). We explore two questions. First, do equity prices of these holding companies reflect the *ELPR* risk of its underlying banks? If investors recognize, at least partially, the latent risk captured by *ELPR*, then lower *ELPR* firms will have higher average implied costs of capital. Second, do equity prices *fully* incorporate the information contained *ELPR*? If investors do not completely impound related information into stock price, then banks with high (low) *ELPR* should earn higher (lower) ex-post returns.

To answer these questions, we need to map banks identified in the FDIC Call Report to their respective publicly-traded holding companies from CRSP. The mapping procedure starts from the CRSP-FRB link table provided by the Federal Reserve Bank of New York.[28] This dataset links regulatory identification numbers (RSSD ID) from the National Information Center (NIC) to the permanent company number (PERMCO) used in CRSP. For each insured institution identified by a unique certificate number (CERT), FDIC provides information on the RSSD ID for both the reporting institution and for its banking holding company. However, the RSSD ID in the CRSP-FRB link table does not necessarily refer to the highest holding company in the regulatory hierarchy. The RSSD ID in the CRSP-FRB link table may belong to the highest ranking corporate parent, or an intermediate corporate parent within the regulatory

[28] https://www.newyorkfed.org/research/banking_research/datasets.html

ownership structure,[29] or the reporting entity itself. Similarly, the RSSD ID of banking holding company provided by the FDIC also may not belong to the highest ranking corporate parent. Therefore, merging the FDIC Call Report dataset with the CRSP-FRB link table using the RSSD ID will result in many incorrectly identified observations.

To create a complete mapping, we utilized the information on organization structures of banking holding companies (BHC), which can be found in FR Y-6 Annual Report. Applying textual analysis methods, we identified all the subsidiaries belonging to each reporting entity in the CRSP-FRB link table. We then matched the RSSD ID of the entity itself, or one of its subsidiaries, to the RSSD ID in the FDIC dataset. This process allowed us to obtain a comprehensive mapping between FDIC Call Report data and CRSP stock return data. After eliminating observations with missing variables, BHCs that are not primarily commercial lenders, and firms with a stock price less than $1, we arrived at a final sample of 6,505 BHC-years over the period 2001-2015.[30]

Appendix VII provides descriptive summary statistics on BHCs by year. Over our sample period, we had an average of 434 BHCs per year. These BHCs had an average market capitalization (MCAP) of 1.453 billion dollars and each controlled, on average, 1.67 commercial banks. Both the number of BHCs and the number of banks have declined over time. Specifically, the number of BHC decreased from 474 in 2001 to 360 in 2015, while the number of banks decreased from 1032 in 2001 to 442 in 2015. The average number of banks owned by each BHC has also declined over time, from 2.18 in 2001 to 1.23 in 2015. Not surprisingly, both MCAP and ROE plummeted during the crisis period. After the crisis, average MACP began to recover and increased to 1.941 billion in 2015,

[29] For example, although the regulatory high-holder of Unionbancal Corporation (PERMCO 841 and RSSD ID 1378434) is Mitsubishi UFJ Financial Group, Inc. (RSSD ID 2961897), the PERMCO 841 is not linked to the regulatory high-holder because Unionbancal Corporation was publicly traded as a separate entity.

[30] To determine a whether a BHC is primarily a commercial lender, we summed the total assets of the lending institutions under its control. If the total assets of these lending subsidiaries summed up to 80% or more of the BHC's total assets, we regarded the BHC as a commercial lender. 238 BHC-year observations were dropped due to this restriction.

which is higher than in the pre-crisis level. Although ROE also showed some sign of recovery after the crisis, it has not returned to pre-crisis levels.

5.1 Implied Cost of Capital

To understand the market's perception of the risk captured by *ELPR*, we examine the relation between each BHC's *ELPR* and its implied cost of capital (ICC). We construct each BHC's *ELPR* by aggregating the corresponding variable across all its controlled banks. Specifically, we compute a BHC's exposure to each loan category by summing up the bank-level holdings for each bank under its control. We then apply the historical variance-covariance matrix of DRs to these holdings (equation (2)) to derive each BHC's *LPR*. For the numerator, we aggregate the book equity of its banking subsidiaries. We then calculate a BHC's *ELPR* based on equation (3). ICC is the discount rate that the market applies to a firm's expected future cash flows in determining its current market value. In other words, it's the required rate of return given the market's assessment of firm risk. If the market perceives *ELPR* as a risk factor, it should assign a higher discount rate to lower *ELPR* firms. We employ following model to test the relationship between *ELPR* and ICC:

$$ICC = \beta_o + \beta_1 R_{ELPR} + \beta_2 SIZE + \beta_3 LEV + \beta_4 MB + Year\ Fixed\ Effects + \varepsilon \quad , \qquad (7)$$

Where ICC is the implied cost of equity estimated in year t. Penman (1998) demonstrated that all equity valuation models can be recast as the dividend discount model with a particular terminal value calculation. We employ a simple form of Penman's generic valuation model, expressed below:

$$MV_t = \frac{DIVIDEND_{t+1}}{1+ICC} + \frac{DIVIDEND_{t+2}}{(1+ICC)^2} + \frac{EARN_{t+2}}{(1+ICC)^2 * ICC} \qquad (8)$$

Where:

MV_t=market value in year t;

$DIVIDEND_{t+1}$, ($DIVIDEND_{t+2}$) = dividends paid during year t+1 (year t+2);

$EARN_{t+2}$ = earnings for year t+2.

An important element in ICC construction is finding a suitable proxy for the market's expectation of future earnings. For our purposes, we invoke rational expectation and assume market has perfect foresight with respect to near-term cash flows (i.e., we use actual reported numbers for $DIVDEND_{t+1}$, $DIVDEND_{t+2}$, and $EARN_{t+2}$). This assumption allows us to focus on the implications of *ELPR* for firms' market implied discount rates without conflating them with errors in cash flow forecasting.

The variable of primary interest in equation (7) is R_{ELPR}, a scaled version of each bank's *ELPR* decile rank. To construct this variable, banks are divided into 10 deciles according to their year-end *ELPR*. We then define R_{ELPR} as the firm's decile rank, minus 1, and then divided by 9. After this transformation, R_{ELPR} ranges from 0 (lowest *ELPR* decile) to 1 (highest *ELPR* decile). If firms' stock prices reflect the riskiness of the underlying loan portfolios as measured by R_{ELPR}, then we should observe a negative coefficient on R_{ELPR}. Following prior studies (Gebhardt, Lee and Swaminathan 2001; Chen et al. 2011), we control for: firm size (SIZE), measured as the natural logarithm of market value; leverage (LEV), computed as the ratio of total long-term debt to total market value of equity; market-to-book ratio (MB); and year fixed effects. All independent variables are calculated using the closest year-end data before the estimation of ICC (i.e., year t-1). Consistent with prior tests, *ELPR* calculation starts from 2001 and ends in 2015; the corresponding period for ICC spans from 2002 to 2016. Robust standard errors are clustered at the bank level.

Table 6 presents results for the implied cost of capital regressions. The first two columns report results for the full sample period (ICC during the period 2002-2016). In model 1, we examine the impact of R_{ELPR} on the implied cost of capital, controlling for year fixed effects. We find that the coefficient on R_{ELPR} is negative and statistically significant at the 1% level, suggesting firms with lower *ELPR* have significantly higher costs of capital. This significant relation continues to hold in model 2, which includes bank-specific control variables (SIZE, LEV and

MB). Economically, the estimated coefficient in Model 2 implies that a move from the lowest *ELPR* decile to the highest *ELPR* decile is associated with an increase in ICC of 1.89%. Given that average cost of equity capital in the U.S. over the long run is between 8 and 12%, this cross-sectional spread is quite economically significant.

Columns 3 and 4 report the results during normal (non-crisis) times. Again we find *ELPR* rank is associated with a lower cost of capital. However, the coefficient on R_{ELPR} is much lower during non-crisis periods than that in the full-sample regression, with the value of 0.0171 in model 3 and 0.0144 in model 4. The last two columns report results for the financial crisis subsample (ICC during the period 2007-2010). We can see that R_{ELPR} loads negatively at the 1 percent level, with a t-statistics of -6.02 in model 5 and -5.25 in model 6. Strikingly, the coefficient on R_{ELPR} in model 6 is -0.0361, indicating that the market imposes a much higher cost of capital on low *ELPR* firms during crisis periods. During the crisis, the lowest *ELPR* banks have a 3.61% higher ICC than highest *ELPR* banks. Overall Table 6 suggests that the implied cost of capital is an important channel through which the market prices *ELPR* and investor awareness about *ELPR* risk increases during an economic downturn.

5.2 *Stock Return Prediction*

We also examine the ability of *ELPR* to predict cross-sectional stock returns. To be specific, we sort all BHCs into deciles based on the value of *ELPR* for each year and examine the realized returns on the resulting portfolios over the next 12 months. To ensure all relevant financial information is already publicly available, we use accounting data from year t to predict stock returns from July year t+1 through June -year t+2. Specifically, we examine annual stock returns for portfolios formed on July- of each year, from 2002 through to 2015.

5.2.1 *Portfolio Returns*

Table 7 reports next 12-month portfolio returns to firms sorted by their *ELPR* and *T1CR*. In these strategies, *ELPR* is adjusted book equity divided by loan portfolio risk (*LPR*), as described in Section 1. *T1CR* is a capital adequacy ratio commonly used by bank regulators, defined as each bank's Tier-1 capital divided by its risk-weighted asset. To construct this table, we sort individual firms by its *ELPR* or *T1CR* measure annually as of June 30. The sample consists of all publicly-traded bank holding companies with at least one FDIC-monitored bank, and 80% or more of its total assets in banking subsidiaries. The top decile contains stocks with the highest *ELPR* score while the bottom decile contains stocks with lowest *ELPR*. Column 1 reports results for the full sample period (holding period returns between July 2002 and June 2017); Column 2 reports results for non-crisis years; and Column 3 reports results for the financial crisis years (holding period returns between July 2007 and June 2011). The bottom rows present tests of differences in mean returns between decile 10 and decile 1 portfolios.

The bottom two rows report returns to a hedged portfolio that goes long in top 10% high *ELPR* (or *T1CR*) firms and sells short the bottom 10% *ELPR* (or*T1CR*) firms. For the full sample period, the difference in mean return between the lowest and highest *ELPR* decile is 6.93% (9.69%-2.76%) and is statistically significant at 1% level (t=4.04). This result suggests that over the full sample period, firms with superior capital adequacy as measured by *ELPR* actually earned higher returns. This is curious for several reasons. First, high *ELPR* firms are less exposed to bank failure risk and one might expect lower average realized returns to reflect their lower risk. Second, we have seen from the ICC tests that these firms on average have lower implied costs of capital. It is curious to see firms with lower ICC earn higher realized returns. Note that these mean returns do not show a monotonic trend across deciles. Further, we do not see a significant difference when firms are sorted by *T1CR.*

Column 2 reports the results for non-crisis periods. We can see that the *ELPR* strategy generates stock returns of -3.78% under normal market conditions. However, the mean returns do not decline in a monotonic way across deciles. Column 3 reports the results for the financial crisis years. For this subsample, we sort BHCs into decile portfolios based on year-end prediction variables between 2006 and 2009 and correspondingly analyze the stock returns from July 2007 to June 2011. As shown, when the economy deteriorates, *ELPR* strongly predicts BHCs' future stock returns. During the crisis, a hedged strategy going long in

BHCs with the highest *ELPR* and selling short those with the lowest *ELPR*, yields 40.21% (=-0.45%+40.66%) per year with a t-statistic of 12.19. The portfolio returns generally exhibit a monotonically increasing trend moving from the lowest to the highest *ELPR* decile. Returns to a *T1CR* strategy much more muted, yielding annualized returns of only 19.98% (t=5.85).

Figure 4 depicts the annual performance of an *ELPR*-based hedged trading strategy for each year in our sample period. Consistent with Table 7, the strategy's performance peaked during the global financial crisis. In contrast, the *ELPR* strategy does not outperform during normal times, even yielding negative hedge returns for many years. However, most of these negative hedge returns are not statistically significant, indicating *ELPR* doesn't have obvious predictive power for returns during normal times.

These results make intuitive sense. During crisis periods, the greater risk exposure of low *ELPR* firms becomes transparent, and investors put more weights on the adequacy of banks' equity capital. Our results show that during such times, the insolvency factor is more fully reflected in the cross-section of stock prices. Our results correspond well with the notion that firms taking greater risk may show higher profits during normal times, but are nonetheless much riskier during periods of economic stress (Meiselman, Nagel, and Purnanandam 2018). Our results are also consistent with mounting prior evidence that various forms of return predictability concentrate in bad times (Cujean and Hasler, 2017; Cen, Wei, and Yang, L., 2016; Henkel, Martin, and Nardari, 2011).[31]

5.2.2 Regression Results

In this section, we further examine whether the predictive ability of ELPR during the poor economic will be subsumed after controlling risk factors widely used in asset pricing. Firstly, we form hedge portfolios long in highest ELPR decile and short in lowest ELPR decile. Following previous studies (e.g., Loughran and

[31] Cujean and Hasler (2017) find that current excess returns and disagreement have better predictive power in bad times. Similarly, Cen, Wei and Yang (2016) find that return predictability using investor disagreement concentrates in bad times. Henkel, Martin, and Nardari (2011) provide evidence that aggregate return predictors such as the dividend and short rate better predict future returns in bad times.

Ritter, 1995), we conduct a set of time-series portfolio regressions using monthly returns for 12 months after the portfolio formation. If the predictability effect of ELPR is merely a manifestation of previously documented confounding effects, then the intercept, representing the excess hedge return, should not be economically and statistically different from zero. The identified risk factors considered include Market ($R_m – R_f$), Size (SMB), Book-to-market (HML), Momentum (MOM), Profitability (RMW) and Investment (CMA). Market is the excess market return over the risk-free rate. SMB is the return on small stock portfolios minus the return on big stock portfolios. HML is the return on the value portfolios minus the return on growth portfolios. MOM is the return on high prior return portfolios minus the return on low prior return portfolios. RMW is the return on robust operating profitability portfolios minus the return on weak operating profitability portfolios. CMA is the return on conservative investment portfolios minus the return on aggressive investment portfolios. More specific definitions can be found in Ken French's data library[32].

Column 1 of table 8 documents the results for Fama-French (1993) three-factor model. We can see that ELPR-based trading strategy has a positive alpha of 4.08 (61.59% annualized), statistically significant at 1% level (t=4.08). In column 2, we augment the Fama-French three-factor model with Carhart's (1997) momentum factor. The results show that the alpha slightly increases to 4.16 (63.08% annualized) with t-statistic of 4.14. The last column presents the results for the Fama-French (2015) five-factor model. Profitability (RMW) loads positively for the hedge strategy, leading alpha decrease to 3.33 (48.16% annualized). To sum up, the results from table 8 provide strong support for our conclusion that the efficacy of *ELPR*-based trading strategy still holds after controlling for common risk factors.

[32] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

6 Robustness tests

In this section, we report results for a battery of robustness tests. For parsimony, we do not include these analyses in the paper. However, they are available upon request.

6.1 Alternative definitions of failure. First, we employ an alternative definition of failure. In the main analyses, we classify all bank closures as failures. Sometimes, regulators may fail to close economic insolvent financial institutions due to other considerations, such as the agency conflicts between regulators and taxpayers (Cole, 1993). Therefore, following Wheelock and Wilson (2000), we define as technical failure any bank with an equity/asset ratio below 0.02. Then, we place both bank closures and technical failures in the fail group and rerun the main tests. This new definition does not alter our conclusion.

6.2 Hazard Models. Because bank failures occur infrequently, a hazard model is a natural alternative to using a logistic regression model. Shumway (2001) points out that hazard models can produce more consistent estimates compared to static models. Therefore, we also employed a Shumway hazard model to examine the classifiers' performances, and found that the results are quite similar to those derived from a logistic regression. However, we note that one limitation of the hazard model is the need to make additional assumptions about the functional model (Ng and Roychowdhury, 2014).

6.3 Cross-Validation Tests. Although we always estimate our model coefficients using historical data prior to the forecast date, it is possible our models are still somewhat informed (and thus contaminated) by the findings of prior studies that used overlapping samples. Cross-validation tests, proposed by Geisser (1975), are commonly used to adjust the bias stemming from in-sample validation (see, for example, Perols, Bowen, Zimmermann, and Samba (2016)). As a robustness check, we performed an out-of-sample ten-fold cross-validation test. This technique randomly splits the whole data set into ten equal folds. One fold is retained as validation data for testing the model, and the remaining 9 folds are used as training data for building the model. The cross-validation process is then repeated 10 times, with each of the 10 folds used exactly once as the validation data. Ultimately, the results over the 10 processes are averaged to produce a single estimation. We find the results estimated from a ten-fold cross-validation test are quite consistent with those of the main test we conducted.

6.4 The Effect of Bank Size. Risk absorption ability differs considerably across large, medium, and small banks (Berger and Bouwman 2009). One possible concern is that our results are driven by the small banks in the sample, because of the predominance of such banks in the U.S. To address this concern, we split our sample into three groups according to bank size (gross total assets, as defined in Berger and Bouwman 2013) and reran our main tests separately for each group. Consistent with their work, we defined small banks as those with gross total assets up to $1 billion; medium banks as those with gross total asset between $ 1 billion and $3 billion; and large banks as those with gross total asset exceeding $ 3 billion. We find that the main results are clearly evident in all three bank size categories.

7 Summary

In this study, we develop, and empirically evaluate, an intuitive and conceptually appealing alternative to the current regulatory risk metrics that we call *Loan Portfolio Risk* (*LPR*). Our approach makes use of the time-varying volatility of default rates for each loan category, as well as the historical cross-correlation structure for these default rates across different loan types. Our results show that the *Equity-to-LPR* ratio (*ELPR*) is additively important in predicting bank failure up to five years in advance, even after controlling for all the CAMELS variables.

Publicly-listed banks with higher *ELPR* have lower market implied costs-of-capital. *ELPR* also strongly predicts cross-sectional stock returns under stress conditions. During the financial crisis (7/2007-6/2011), a cash-neutral strategy that longs high-*ELPR* and shorts low-*ELPR* banks yields a monthly alpha of 3.3% to 4.2%. We conclude *LPR* captures key aspects of bank risk missed by a risk-weighted-asset approach.

As an alternative regulatory measure of capital adequacy, *ELPR* at least three clear advantages over the risk-weighted asset (RWA) approach. First, by focusing on the time-varying *variance* in default risk for the portfolio as a whole, *ELPR* captures an important intertemporal dimension of bank risk that is clearly missing from the RWA-based metrics. This is evident from the exceptional performance of *ELPR* in bank failure predictions as well as its correlation with market-based risk metrics during periods of economic distress.

Second, *ELPR* is more straightforward to calculate and more objective than many RWA-based metrics. Because it can be updated quickly using only each bank's quarterly call report, *ELPR* alleviates some of the moral hazard problems associated with the internal-rate based (IRB) methods. Third, because *ELPR* is based on the long-run variance of delinquency rates rather than the most recent quarterly estimates, it will significantly mitigate the procyclical concerns associated with IRB-based estimates (Andersen 2011; Behn et al. 2016; Kashyap and Stein 2004). In other words, using *ELPR* to measure capital adequacy means banks are less likely to be forced to cut back on their lending activity in bad times, thereby contributing to a worsening of the initial downturn.

Ten years after the collapse of Lehman Brothers, experts agree that an important cause of the global financial crisis was the underestimation of downside risk in the period leading to that fateful September 14, 2008 event (see Gennaioli and Shleifer 2018). Market-wide expectations for economic growth were too optimistic and the risk building up in the financial system was not fully factored into asset prices. The Lehman bankruptcy had enormous impact precisely because it triggered a major correction in these expectations.

Our study provide a novel and more economically sensible measure of banks' default risk. We recognize this is a small step forward in the much broader problem of bank regulation. However, we believe our study illustrates the potential of alternative risk metrics that reflect portfolio-level default volatility. Our hope and expectation is that our analysis will stimulate further research along such lines.

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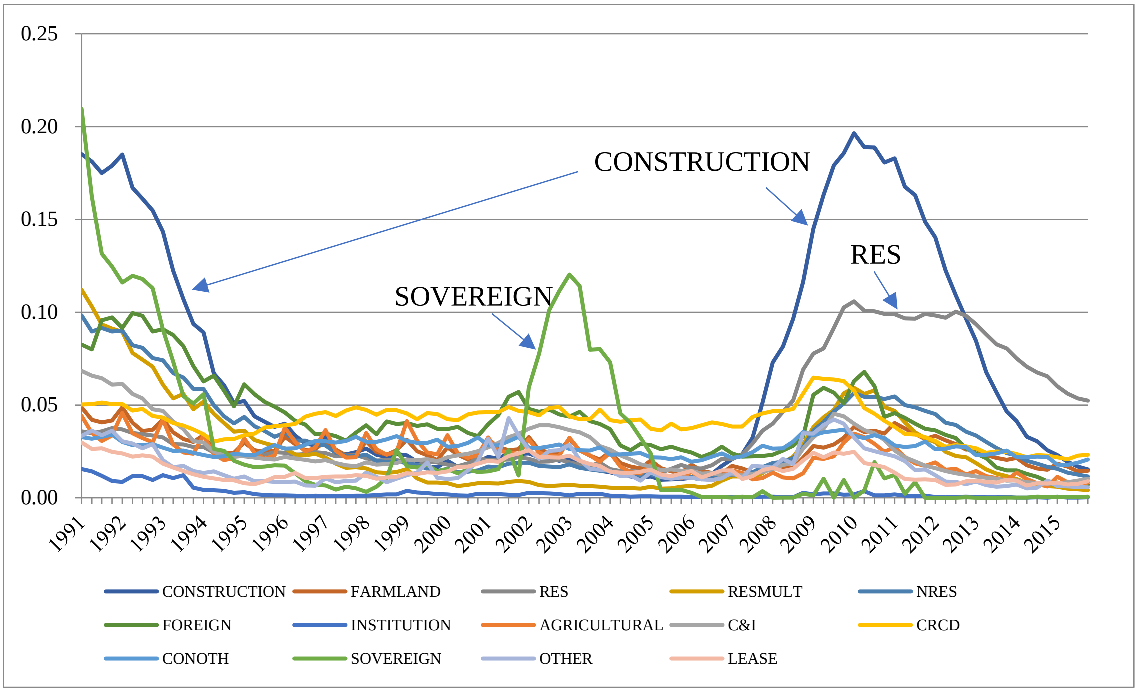
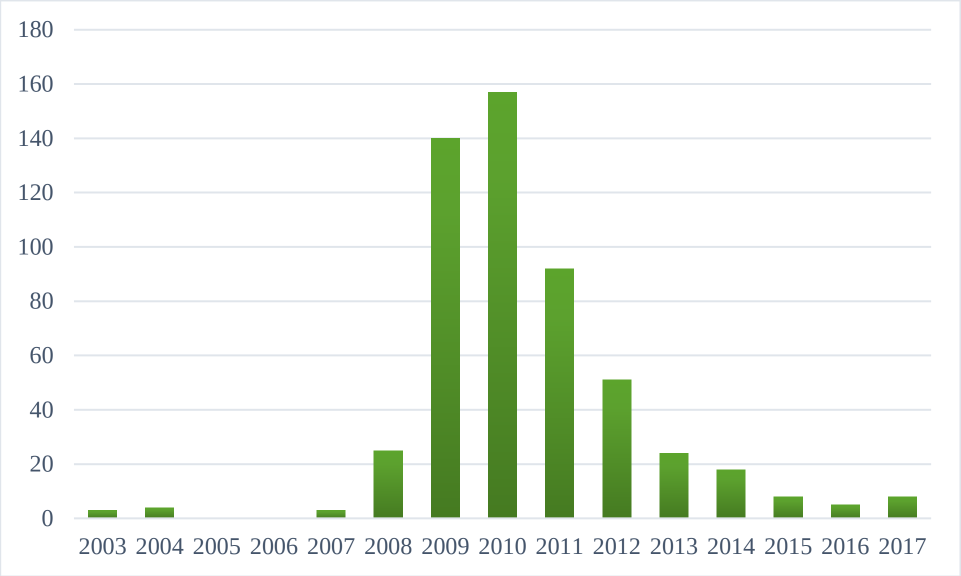
Figure 1. Aggregate delinquency rates by loan type over time



This figure depicts time-series plots of quarterly aggregate delinquency ratios by different loan types from 1991Q1 to 2015Q4. The delinquency ratio is calculated as aggregate non-performing loans divided by aggregate total loans for each loan category. These statistics are aggregated across all FDIC-insured institutions for each quarter. We obtain the relevant information from FDIC Quarterly Banking Profile. Appendix IV provides a more detailed definition of each loan type.

Figure 2. The Number of Bank Failures by Year



This figure presents the frequency of bank failures in the United States from 2003 to 2017. Our sample includes all FDIC insured banks and thrifts (including savings and loans associations and savings banks). Source: *the FDIC Failed Institutions List*.

Figure 3. Receiver Operating Characteristic (ROC) curves

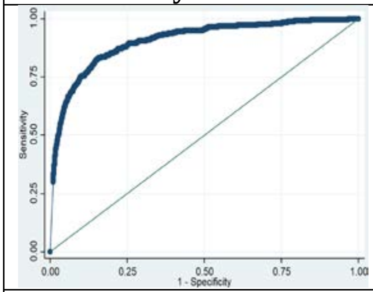
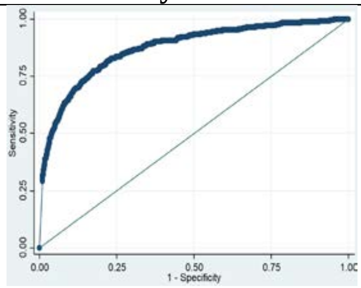
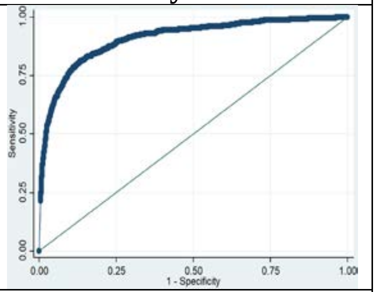
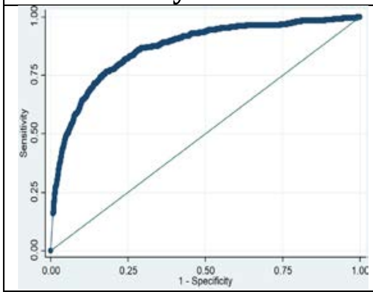
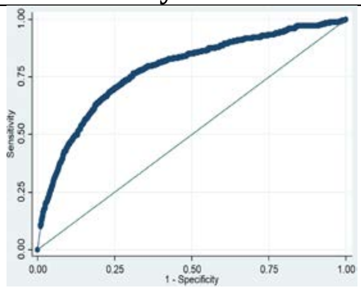
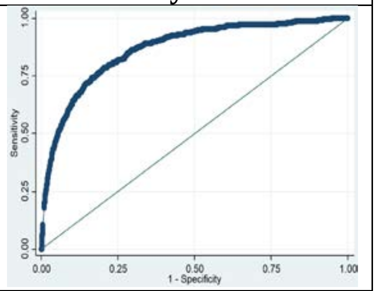
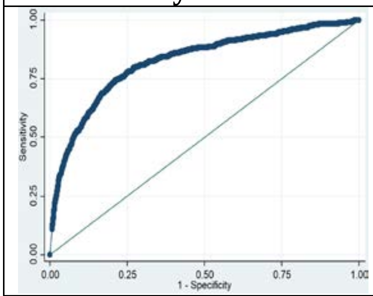
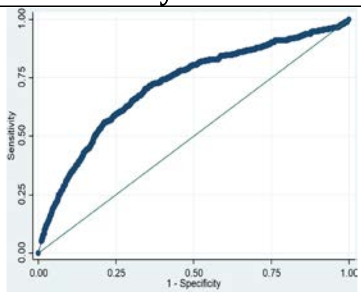
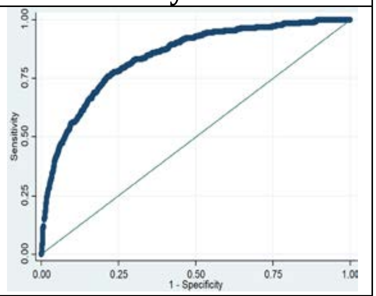
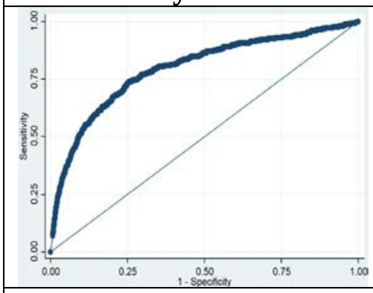
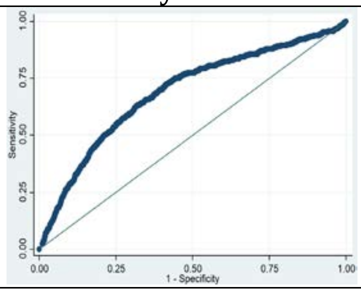
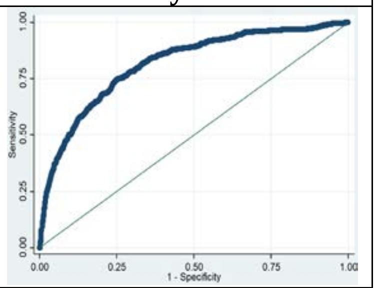
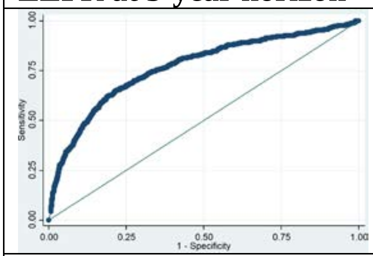
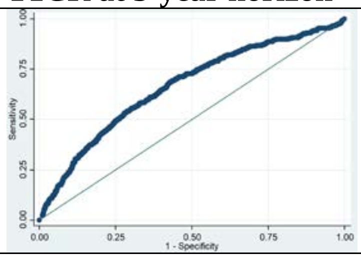
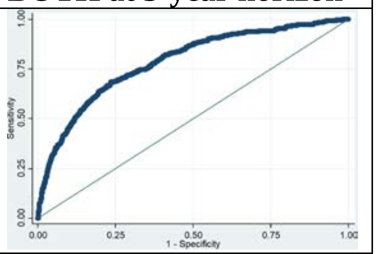
ELPR at 1-year horizon	T1CR at 1-year horizon	BOTH at 1-year horizon
		
AUC=0.9045	*AUC=0.8722*	*AUC=0.9073*
ELPR at 2-year horizon	**T1CR at 2-year horizon**	**BOTH at 2-year horizon**
		
AUC=0.8639	*AUC=0.7802*	*AUC=0.8658*
ELPR at 3-year horizon	**T1CR at 3-year horizon**	**BOTH at 3-year horizon**
		
AUC=0.8237	*AUC=0.7155*	*AUC=0.8423*
ELPR at 4-year horizon	**T1CR at 4-year horizon**	**BOTH at 4-year horizon**
		
AUC=0.7945	*AUC=0.6869*	*AUC= 0.8148*
ELPR at 5-year horizon	**T1CR at 5-year horizon**	**BOTH at 5-year horizon**
		
AUC= 0.7666	*AUC=0.6614*	*AUC=0.7856*

Figure 3 depicts curves from a receiver operating characteristics (ROC) analysis across different horizons, based on different prediction models. The diagonal line in each graph divides the ROC space and illustrates the appearance of a ROC curve for a naive model with no classification power. Points above the diagonal line represent good classification results (better than random) while points below the line represent bad results (worse than random). AUC is the area under the ROC curve. A higher value of AUC indicates a model with stronger ability to distinguish between failures and survivors. ELPR is the ratio of shareholder equity to amount of loan portfolio risk in logarithmic form, as described in section 1. T1CR is tier 1 risk-based capital ratio as defined by regulator. Specifically it is the bank's Tier-1 capital divided by its risk-weighted asset. BOTH represents the combination of ELPR and T1CR.

Figure 4. Annual hedged returns to an *ELPR*-based strategy

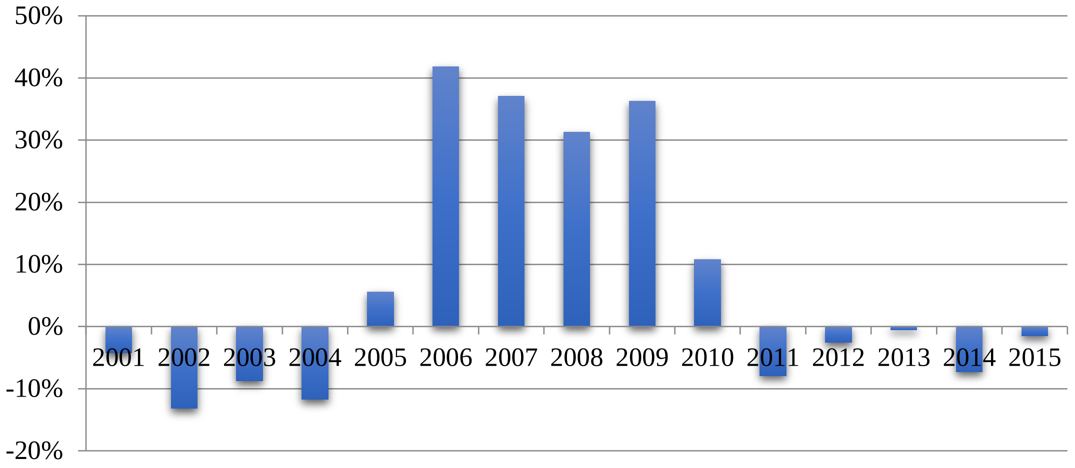


Figure 4 depicts the yearly hedged returns to an ELPR-based trading strategy. The strategy is implemented using financial data reported by publicly-traded bank holding companies (BHCs) during the period 2001-2015 (corresponding to portfolio holding periods from July 2002 to June 2017). The hedged return is the difference in mean returns between an equal-weighted portfolio of BHCs in the highest *ELPR* decile and those in the lowest *ELPR*. *ELPR* is the ratio of shareholder equity to amount of loan portfolio risk in logarithmic form for each BHC, as described in section 1.

Table 1. U.S. Bank Failures from 2003 to 2017

Year	Num of Banks	Num of Failures	Failure Rate	Estimated Loss (in $ thousands)
2003	9,354	3	0.03%	62,646
2004	9,181	4	0.04%	3,917
2005	8,976	0	0.00%	0
2006	8,833	0	0.00%	0
2007	8,680	3	0.03%	161,851
2008	8,534	25	0.29%	1,8160,993
2009	8,305	140	1.69%	26,957,643
2010	8,012	157	1.96%	16,359,499
2011	7,658	92	1.20%	6,617,073
2012	7,357	51	0.69%	2,461,603
2013	7,083	24	0.34%	1,247,973
2014	6,812	18	0.26%	392,245
2015	6,509	8	0.12%	866,542
2016	6,182	5	0.08%	47,114
2017	5,913	8	0.14%	1,132,364
Total		538		74,471,463

This table provides descriptive statistics for U.S. bank failures between 2003 and 2017. Column 1 reports the number of FDIC insured banks and thrifts (including savings and loans associations and saving banks) at the beginning of each year. Column 2 reports the number of bank failures that occurred during the year. Column 3 reports failures as a percentage of banks that existed at the beginning of the year. Column 4 reports the estimated loss arising from these failures. This estimated loss is obtained from the FDIC Failed Institutions report, and represents the difference between the amount disbursed from the Deposit Insurance Fund (DIF) to cover obligations to depositors and the amount recoverable from the liquidation of the receivership estate. These estimates are routinely adjusted with updated information from new appraisals and asset sales, which ultimately affect the asset values and projected recoveries. The estimated loss reported above are as of December 31, 2017. (Source: *the FDIC Failed Institutions List*.)

Table 2.

Panel A. Correlations of Aggregate Delinquency Rates across Loan Categories

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
(1)	CONSTRUCTION	1.00													
(2)	FARMLAND	***0.75******	1.00												
(3)	RES	***0.66******	0.25*	1.00											
(4)	RESMULT	***0.86******	***0.82******	0.26**	1.00										
(5)	NRES	***0.86******	***0.86******	0.31**	***0.98******	1.00									
(6)	FOREIGN	***0.63******	***0.81******	-0.08	***0.84******	***0.84******	1.00								
(7)	INSTITUTION	***0.54******	***0.69******	-0.14	***0.82******	***0.82******	***0.86******	1.00							
(8)	AGRICULTURAL	0.38***	***0.84******	-0.19	***0.59******	***0.59******	***0.76******	***0.62******	1.00						
(9)	C&I	***0.62******	***0.77******	-0.06	***0.79******	***0.76******	***0.89******	***0.83******	***0.72******	1.00					
(10)	CRCD	0.30**	0.33***	-0.18	0.33***	0.21*	***0.50******	0.31**	***0.51******	***0.62******	1.00				
(11)	CONOTH	***0.51******	***0.53******	0.20*	0.44***	0.38***	0.47***	0.28**	***0.54******	***0.55******	***0.78******	1.00			
(12)	SOVEREIGN	0.30**	***0.57******	-0.29**	***0.58******	***0.57******	***0.69******	***0.80******	***0.56******	***0.83******	0.31**	0.19	1.00		
(13)	OTHER	***0.60******	***0.55******	0.15	***0.56******	0.49***	***0.63******	0.49***	0.47***	***0.80******	***0.74******	***0.65******	0.48***	1.00	
(14)	LEASE	0.42***	***0.50******	-0.10	0.49***	0.41***	***0.63******	***0.56******	***0.53******	***0.86******	***0.77******	***0.59******	***0.65******	***0.89******	1.00

This panel reports the pairwise Pearson correlations for quarterly delinquency ratios across different loan types. The sample period includes 1991 Q1 to 2015 Q4 (100 quarterly observations). The delinquency ratio is calculated as aggregate non-performing loans divided by aggregate total loans for each loan category. We obtain the relevant information from the FDIC Quarterly Banking Profile. Please refer to Appendix IV for the detailed definition of each loan type. Correlation coefficients shown in bold and italic are higher than 0.5. ***, **, and * denote significance at the 0.001, 0.01, and 0.05 levels, respectively.

Panel B. Variance-covariance Matrix of Aggregate Delinquency Rates across Loan Categories

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
(1)	CONSTRUCTION	38.58													
(2)	FARMLAND	3.85	0.68												
(3)	RES	12.23	0.63	8.97											
(4)	RESMULT	13.30	1.68	1.97	6.17										
(5)	NRES	12.00	1.59	2.07	5.45	5.04									
(6)	FOREIGN	8.73	1.49	-0.56	4.61	4.19	4.91								
(7)	INSTITUTION	1.15	0.20	-0.14	0.70	0.63	0.65	0.12							
(8)	AGRICULTURAL	2.20	0.64	-0.52	1.36	1.22	1.56	0.19	0.86						
(9)	C&I	5.38	0.90	-0.26	2.76	2.39	2.78	0.40	0.94	1.97					
(10)	CRCD	1.82	0.27	-0.53	0.80	0.47	1.06	0.10	0.46	0.84	0.93				
(11)	CONOTH	1.38	0.19	0.27	0.48	0.37	0.46	0.04	0.22	0.34	0.33	0.19			
(12)	SOVEREIGN	8.05	2.04	-3.80	6.21	5.58	6.65	1.18	2.23	5.03	1.29	0.36	18.76		
(13)	OTHER	3.64	0.44	0.44	1.36	1.07	1.37	0.16	0.43	1.10	0.70	0.28	2.04	0.96	
(14)	LEASE	1.48	0.23	-0.17	0.69	0.52	0.79	0.11	0.28	0.68	0.42	0.15	1.59	0.49	0.32

This panel reports the variance-covariance matrix for quarterly delinquency ratios across different loan types. The delinquency ratio is calculated as aggregate non-performing loans divided by aggregate total loans for each loan category. Table values in the diagonal are time-series variances of the quarterly default rates for each category; off-diagonal variables are pair-wise covariance terms. We obtain default rate information from the FDIC Quarterly Banking Profile reports. Each number is multiplied by 10,000 for ease of exposition. The sample period used in constructing this table includes 1991 Q1 to 2015 Q4 (100 quarterly observations). Appendix IV provides the detailed definition of each loan type.

Table 3. Bank Failure Prediction: *ELPR* vs. *T1CR*

Panel A 1-Year Horizon

	ELPR	*T1CR*	*BOTH*
ELPR	-4.439***		-3.669***
	(-22.95)		(-17.92)
T1CR		-65.274***	-18.000***
		(-10.85)	(-4.10)
Constant	2.563***	2.190***	3.311***
	(9.24)	(3.68)	(8.34)
Observations	111453	111453	111453
Pseudo R2	***0.247***	***0.171***	***0.255***
Incremental Power of ELPR			***8.4%***

Panel B 2-Year Horizon

	ELPR	*T1CR*	*BOTH*
ELPR	-3.285***		-3.634***
	(-20.25)		(-23.52)
T1CR		-22.407***	6.173***
		(-5.14)	(4.32)
Constant	0.970***	-2.292***	0.799***
	(3.79)	(-4.44)	(3.18)
Observations	101557	101557	101557
Pseudo R2	***0.173***	***0.055***	***0.177***
Incremental Power of ELPR			***12.2%***

Panel C 3-Year Horizon

	ELPR	*T1CR*	*BOTH*
ELPR	-2.589***		-3.282***
	(-17.19)		(-22.26)
T1CR		-7.157***	9.141***
		(-3.47)	(12.53)
Constant	-0.046	-4.085***	-0.026
	(-0.18)	(-14.16)	(-0.12)
Observations	92014	92014	92014
Pseudo R2	***0.128***	***0.015***	***0.148***
Incremental Power of ELPR			***13.3%***

Panel D 4-Year Horizon

	ELPR	*T1CR*	*BOTH*
ELPR	-2.103***		-2.791***
	(-14.41)		(-19.47)
T1CR		-5.039***	8.463***
		(-3.21)	(13.64)
Constant	-0.784***	-4.318***	-0.656***
	(-3.00)	(-18.79)	(-3.04)
Observations	82828	82828	82828
Pseudo R2	***0.098***	***0.009***	***0.118***
Incremental Power of ELPR			***10.9%***

Panel E 5-Year Horizon

	ELPR	*T1CR*	*BOTH*
ELPR	-1.746***		-2.408***
	(-12.98)		(-18.14)
T1CR		-3.921***	7.729***
		(-2.87)	(13.09)
Constant	-1.323***	-4.402***	-1.118***
	(-5.23)	(-21.37)	(-5.42)
Observations	74038	74038	74038
Pseudo R2	***0.077***	***0.007***	***0.096***
Incremental Power of ELPR			***8.9%***

This table reports the results from a set of logistic regressions of bank failure indicators on predictor variables across various prediction horizons. The predictor variables in Panels A-E are measured at the year-end over 1- to 5-year horizon, respectively. Predictor variables are ELPR, T1CR and the combination of these two variables in model (1), model (2) and model (3) in each table. ELPR is the ratio of shareholder equity to amount of loan portfolio risk in logarithmic form, as described in section 1. T1CR is tier 1 risk-based capital ratio as defined by regulator. Specifically it is the bank's Tier-1 capital divided by its risk-weighted asset. The bottom two rows of each table present the Pseudo-R^2 for each model and the incremental explanatory power of ELPR relative to T1CR. The t-statistics in parentheses are based on standard errors clustered at the bank level. *, **, *** indicate statistical significance at the 10 percent, 5 percent, and 1 percent levels for two-tailed tests, respectively.

Table 4. Pseudo R^2 and Accuracy Rate: *ELPR* vs. CAMELS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	ELPR	C	A	M&E	L	S	CAMELS	Combined
1-year Horizon								
Pseudo R^2	0.247	0.171	0.188	0.156	0.004	0.004	0.333	0.375
Accuracy rate	80.91%	74.44%	69.22%	67.58%	18.58%	12.08%	86.00%	88.74%
2-year Horizon								
Pseudo R^2	0.173	0.055	0.050	0.050	0.015	0.000	0.142	0.229
Accuracy rate	72.78%	56.04%	32.57%	36.50%	35.22%	4.91%	68.70%	79.36%
3-year Horizon								
Pseudo R^2	0.128	0.015	0.003	0.013	0.020	0.007	0.068	0.171
Accuracy rate	64.74%	43.09%	-1.66%	13.56%	38.52%	16.96%	54.36%	72.24%
4-year Horizon								
Pseudo R^2	0.098	0.009	0.001	0.002	0.016	0.013	0.050	0.135
Accuracy rate	58.90%	37.38%	14.07%	2.46%	33.96%	21.11%	46.17%	65.14%
5-year Horizon								
Pseudo R^2	0.077	0.007	0.002	0.003	0.009	0.014	0.042	0.108
Accuracy rate	53.31%	32.27%	19.66%	6.77%	25.46%	22.06%	41.27%	59.13%

This table reports the pseudo R^2s and Accuracy Rates (ARs) derived from bank failure prediction models that feature *ELPR* and CAMELS-related variables. Model 1 uses *ELPR* as a stand-alone input variable. Accuracy rate (AR) is a composite measure that combines a model's type-1 and type-2 error rates. It is based on the area under the ROC curve (AUC): AR=2×AUC-1. *ELPR* is the ratio of shareholder equity to amount of loan portfolio risk in logarithmic form, as described in section 1. CAMELS variables are used by regulators to monitor bank health and are defined in Appendix V. Models 2-6 use each individual component of CAMELS as input on a stand-alone basis. Model 7 uses all CAMELS variables together. Model 8 combines all CAMELS proxies with *ELPR* to predict bank failures. Results are separately reported for 1-year to 5-year forecasting horizons.

Table 5. Variance-related Information and Covariance-related Information

Panel A

	1-year	2-year	3-year	4-year	5-year
VAR_unq	***-3.606******	***-3.689******	***-3.572******	***-3.271******	***-3.229******
	(-11.85)	***(-14.27)***	***(-15.10)***	***(-13.03)***	***(-12.66)***
COVAR	*-1.987****	*-2.639****	*-2.612****	*-2.276****	*-1.822****
	(-8.07)	*(-14.91)*	*(-14.95)*	*(-13.80)*	*(-11.99)*
CAMELS	Control	Control	Control	Control	Control

Panel B

	1-year	2-year	3-year	4-year	5-year
COV_unq	***-1.510*****	***-2.143******	***-1.980******	***-1.218*****	***-0.333***
	(-2.25)	***(-4.27)***	***(-4.24)***	***(-2.54)***	***(-0.75)***
VAR	*-2.408****	*-2.853****	*-2.780****	*-2.359****	*-1.977****
	(-11.02)	*(-18.54)*	*(-18.98)*	*(-16.12)*	*(-14.73)*
CAMELS	Control	Control	Control	Control	Control

This table examines the relative importance of variance- and covariance-related information conveyed by *ELPR*. The table values represent the results of a set of logistic regression models to predict bank failures. The dependent variable is an indicator for future bank failure in year $t+i$, where i = 1 (column 1) to 5 (column 5). The independent variable of particular interest is either *VAR_unq* (in Panel A), or *COV_unq* (in Panel B). *VAR_unq* is the unique variance-related information in *ELPR* after controlling for the information in *COVAR*; and *COV_unq* is the covariance-related information in *ELPR* after controlling for the information in *VAR*. The independent variable in each regression is first orthogonalized with respect to the other regressor, (see construction details in Section 4.4). For all estimations, we include the CAMELS variables as control. The t-statistics in parentheses are based on standard errors clustered at the bank level. *, **, *** indicate statistical significance at the 10 percent, 5 percent, and 1 percent levels for two-tailed tests, respectively.

Table 6. *ELPR* Rank and the Market Implied Cost of Capital (ICC) for Publicly-listed Bank Holding Companies

	Full Sample Period		Non-Crisis		Financial Crisis	
	(1)	(2)	(3)	(4)	(5)	(6)
$\boldsymbol{R_{ELPR}}$	***-0.0235****	***-0.0189****	***-0.0171****	***-0.0144****	***-0.0475****	***-0.0361****
	(-8.13)	***(-7.29)***	***(-6.79)***	***(-6.09)***	***(-6.02)***	***(-5.25)***
SIZE		-0.0006		-0.0002		-0.0021*
		(-0.98)		(-0.31)		(-1.72)
LEV		0.0101***		0.0099***		0.0099***
		(9.16)		(7.79)		(4.67)
MB		-0.0045***		-0.0029**		-0.0103***
		(-3.06)		(-2.03)		(-2.72)
Constant	0.0945***	0.0950***	0.0913***	0.0882***	0.0851***	0.1035***
	(48.30)	(24.69)	(50.06)	(23.69)	(15.26)	(10.64)
Observations	4936	4936	3721	3721	1215	1215
Year FE	YES	YES	YES	YES	YES	YES
Adjusted R^2	0.193	0.280	0.232	0.301	0.131	0.240

This table reports results from pooled regressions of firms' implied cost of capital (ICC) on their scaled *ELPR* rank (R_{ELPR}) and controls. The sample consists of all publicly traded financial service firm with at least one FDIC-monitored bank. Columns 1 and 2 report results for the full sample period (2002-2016), columns 3 and 4 report results for non-crisis periods (2002-2006; 2011-2016) and columns 5 and 6 report results for the financial crisis years (2007-2010). The dependent variable is each firm's implied cost of capital (ICC), estimated using equation (8). R_{ELPR} is a scaled decile rank measure where we subtract 1 from each firm's year-end *ELPR* decile rank, and divide the result by 9. By construction, this variable ranges from 0 to 1, and the estimated coefficient captures the difference in mean between the Decile 1 and Decile 10 firms. The control variables are: Bank size (SIZE), defined as the natural logarithm of the equity market value; the market-to-book ratio (MB), measured as of the last fiscal year-end; and Bank leverage (LEV), defined as the ratio of long-term debt to market value of equity. The t-statistics in parentheses are based on standard errors clustered at the bank level. *, **, *** indicate statistical significance at the 10 percent, 5 percent, and 1 percent levels for two-tailed tests, respectively.

Table 7. Average Next-Twelve-Month Returns for *ELPR* Decile Portfolios

	Full Sample Period (7/2002-6/2017)	Non-Crisis Years (7/2002-6/2007; 7/2011-6/2017)	Financial Crisis Period (7/2007-6/2011)
ELPR Deciles	RET	RET	RET
1	2.76%	17.43%	-40.66%
(Low)	(1.82)	(14.26)	(-14.36)
2	6.33%	18.1%	-25.99%
	(4.79)	(16.44)	(-9.20)
3	6.21%	17.89%	-25.15%
	(4.80)	(16.77)	(-9.06)
4	8.11%	16.77%	-15.44%
	(6.71)	(15.65)	(-5.58)
5	6.55%	15.00%	-15.43%
	(5.85)	(15.34)	(-6.00)
6	9.15%	16.09%	-9.38%
	(8.85)	(17.44)	(-3.77)
7	7.95%	13.49%	-6.89%
	(7.94)	(14.13)	(-2.89)
8	8.91%	14.09%	-4.76%
	(9.33)	(14.57)	(-2.30)
9	8.52%	12.27%	-1.23%
	(10.22)	(14.06)	(-0.68)
10	9.69%	13.65%	-0.45%
(High)	(11.37)	(15.43)	(-0.24)
High-Low	***6.93%***	***-3.78%***	***40.21%***
(ELPR strategy)	***(4.04)***	***(2.52)***	***(12.19)***
High-Low	***2.42%***	***-2.90%***	***19.98%***
(T1CR strategy)	***(1.59)***	***(2.14)***	***(5.85)***

This table examines next 12-month portfolio returns to firms sorted by their *ELPR* and *T1CR*. In these strategies, *ELPR* is adjusted book equity divided by loan portfolio risk (*LPR*), as described in Section 1. *T1CR* is a capital adequacy ratio commonly used by bank regulators, defined as each bank's Tier-1 capital divided by its risk-weighted asset. To construct this table, we sort individual firms by its *ELPR* or *T1CR* measure annually as of June 30. The sample consists of all publicly-traded bank holding companies with at least one FDIC-monitored bank, and 80% or more of its total assets in banking subsidiaries. The top decile contains stocks with the highest *ELPR* score while the bottom decile contains stocks with lowest *ELPR*. Column 1 reports results for the full sample period (holding period returns between July 2002 and June 2017); Column 2 reports results for non-crisis years; and Column 3 reports results for the financial crisis years (holding period returns between July 2007 and June 2011). The bottom rows present tests of differences in mean returns between decile 10 and decile 1 portfolios. T-statistics are reported in parentheses.

Table 8. Average Monthly Returns to an *ELPR*-based hedge strategy during the Financial Crisis (2007-11), after Controlling for Common Risk Factors

	(1)	(2)	(3)
	Fama French three-Factor	Carhart Four-Factor	Fama French Five-Factor
Alpha	***4.0830******	***4.1645******	***3.3322******
	(4.08)	***(4.14)***	***(3.21)***
R_m-R_f	-0.0040	0.0441	0.2627
	(-0.02)	(0.21)	(1.14)
SMB	-0.2317	-0.2354	-0.4337
	(-0.52)	(-0.53)	(-0.99)
HML	-0.7898**	-0.6849*	-0.9096**
	(-2.44)	(-1.99)	(-2.50)
MOM		0.1480	
		(0.91)	
RMW			1.1611*
			(1.69)
CMA			1.0382
			(1.44)
Observations	48	48	48
Adjusted R^2	0.136	0.132	0.188

This table reports the results of time-series regression of monthly portfolio hedge returns to ELPR strategy on well-documented risk factors. The regression has 48 observations from July 2007 until June 2011, inclusively. Common risk factors considered include Market (R_m–R_f), Size (SMB), Book-to-market (HML), Momentum (MOM), Profitability (RMW) and Investment (CMA). Market is the excess market return over the risk-free rate; SMB is the return on small stock portfolios minus the return on big stock portfolios; HML is the return on the value portfolios minus the return on growth portfolios; MOM is the return on high prior return portfolios minus the return on low prior return portfolios; RMW is the return on robust operating profitability portfolios minus the return on weak operating profitability portfolios; CMA is the return on conservative investment portfolios minus the return on aggressive investment portfolios. Models 1-3 document the results for Fama French three-Factor model(1993), Carhart Four-Factor model (1997), and Fama French Five-Factor model (2015), separately. T-statistics are reported in parentheses. *, **, *** indicate statistical significance at the 10 percent, 5 percent, and 1 percent levels for two-tailed tests, respectively.

Appendix I. A Timeline of Basel Pronouncements

Basel I:

Asset Risk Weighting System:

The Risk Weighted Assets (RWA) of a financial institution is defined as the linear sum of its holdings in each asset class, each multiplied by a fixed risk weight:

- 0% (e.g., sovereign debts)
- 20% (e.g., receivables from other banks)
- 50% (e.g., mortgages)
- 100% (e.g., other corporate receivables)

Basel II:

Background:

Basel II was developed in response to perceived shortcomings in Basel I, particularly with the asset risk weighting system (too arbitrary, static, insensitive variations in risk within each asset group). It allowed some, larger, banks a second, more flexible, way to estimate its risk exposure.

Risk Weights:

1) Standardized approach:
   Similar to Basel I, but with more granular risk categories.
2) Advanced approach (Internal Ratings-based approach, IRB)
   Core banks and Opt-in banks are allowed to determine some of the key elements needed to calculate their own capital requirements: probability of default (PD), loss given default (LGD), exposure at default (EAD), or effective maturity (M). The risk parameters are then put into a formula provided by regulators and then transformed to K (the risk weight for each asset class)

IRB Application:

1) Core banks (required): (i) total assets>=$250 billion or (ii) foreign exposure >=$10 billion; (2) Opt-in banks: banks that voluntarily adopt advanced approaches; 3) A subsidiary of a core bank or opt-in bank.

Property-Portfolio Invariance:

Note that under Basel II, the risk-based capital requirement for a particular exposure still does not depend on the other property exposures held by the bank. Under both the Standardized approach and the IRB-based approach, the total capital at risk for the bank is simply the sum of the risk-weighted capital for each individual exposure.

Basel III:

Background:

Basel III was developed in response to the global financial crisis, which highlighted many shortcomings of the IRB-based approaches (easy to manipulate, inconsistent, opaque, complicated).

Nature of Revisions:

1) To enhance the robustness and risk sensitivity of the standardized approaches
2) To constrain the use of the IRB-based methods.
 (i) Removed the option to use the advanced IRB approach for certain asset classes;
 (ii) Adopted "input" floors (for metrics such as probabilities of default (PD) and loss-given-default (LGD)) to ensure a minimum level of conservativism in model parameters for asset classes where the IRB approaches remain available;
 (iii) Provided greater specificity in terms of appropriate parameter estimation practices to reduce RWA variability.

Appendix II. Prompt Corrective Action (PCA) Guidelines

Prompt Corrective Action (PCA) guidelines were issued by the FDIC to establish the capital measures and threshold levels that are used to determine supervisory actions. The following table summarizes the threshold values used to define PCA categories before Basel III and under Basel III, respectively. Banks in the three lowest PCA categories –Undercapitalized; Significantly Undercapitalized; or Critically Undercapitalized – are subject to a variety of possible regulatory interventions. If a bank is Critically Undercapitalized, the PCA framework generally prohibits the payment of interest on subordinated debt. Further, no later than 90 days after a bank becomes Critically Undercapitalized, its primary Federal banking agency will either (i) appoint a receiver or (ii) require other action (for an extendable period up to an additional 180 days) that it determines better achieves the purposes of the PCA framework. In these tables, Total risk-based capital is (Tier-1 capital + Tier-2 capital)/RWA; *T1CR* is Tier-1 capital divided by RWA; Leverage capital is Tier-1 capital divided by total assets; and Common equity Tier-1 risk-based capital is (Tier-1 capital – additional Tier-1 capital)/RWA. In all cases RWA is risk-weighted assets as defined by Basel guidelines.

PCA Capital Categories (before Basel III)

Capital category	**Total risk-based capital**	**Tier-1 risk-based capital (*T1CR*)**	**Leverage capital**
Well capitalized	10%	6%	5%
Adequately capitalized	8%	4%	4%
Undercapitalized	< 8%	< 4%	< 4%
Significantly undercapitalized	< 6%	< 3%	<3%
Critically undercapitalized	Tangible Equity / Total Assets <= 2%		

PCA Capital Categories (under Basel III)

Capital category	**Total risk-based capital**	**Tier-1 risk-based capital**	**Common Equity Tier-1 risk-based capital**	**Leverage capital**
Well capitalized	10%	8%	6.5%	5%
Adequately capitalized	8%	6%	4.5%	4%
Undercapitalized	< 8%	< 6%	<4.5%	< 4%
Significantly undercapitalized	< 6%	< 4%	3%	<3%
Critically undercapitalized	Tangible Equity / Total Assets <= 2%			

Appendix III. Main Components of Bank Assets

This appendix provides a breakdown of the two main components on the asset side of banks' balance sheets: loan portfolios and debt securities (typically government debt).

Our sample consists of all FDIC-insured banks and thrift companies that filed regulatory reports in the years 2001 to 2015, inclusively. The unit of observation is a firm-year. To construct this appendix, we sort all banks into ten size deciles based on their total asset, as reported at the end of each calendar year. Decile 1 (10) represents the largest (smallest) banks by total assets. For each size decile, we report the size of their loan portfolio and the amount of their debt securities, each expressed as a percentage of total assets.

Column 1 (2) reports the mean (median) loan portfolio as a percentage of each bank's total assets; Column 3 (4) reports the mean (median) debt securities as a percentage of each bank's total assets. The corresponding statistics for all FDIC-insured banks in our sample, without conditioning on size, are presented in the bottom line.

Bank Size Deciles by Total Asset	Loan (Mean)	Loan (Median)	Debt securities (Mean)	Debt securities (Median)
1 (largest)	65.74%	68.11%	20.93%	18.55%
2	67.62%	69.66%	19.98%	17.71%
3	66.23%	68.47%	20.96%	18.27%
4	66.20%	68.03%	20.59%	18.50%
5	65.16%	66.86%	21.38%	18.88%
6	64.35%	66.44%	21.47%	19.01%
7	62.51%	64.33%	22.50%	20.34%
8	61.25%	62.96%	22.98%	20.76%
9	59.20%	60.57%	23.50%	21.39%
10 (smallest)	55.49%	56.67%	22.59%	20.58%
Total	63.37%	65.51%	21.69%	19.23%

Appendix IV. Loan Categories and Delinquency Rates

This appendix presents summary statistics for loan categories. The sample consists of 111,453 bank-year observations from 2001 to 2015. To construct this table, we use data from FDIC Quarterly Banking Profile (QBP) reports to create 14 loan categories:

Loan type	Definitions
CONSTRUCTION	Construction and development loans.
FARMLAND	Real estate loans secured by farmland.
RES	Real estate loans secured by 1-4 family residential properties.
RESMULT	Real estate loans secured by multifamily residential properties.
NRES	Real estate loans secured by nonfarm nonresidential properties.
FOREIGN	Real estate loans in foreign offices.
INSTITUTION	Loans to depository institutions.
AGRICULTURAL	Agricultural production loans.
C&I	Commercial & industrial loans.
CRCD	Credit cards.
CONOTH	Other loans to individuals.
SOVEREIGN	Loans to foreign governments and official institutions.
OTHER	All other loans.
LEASE	Lease financing receivables.

We present summary statistics for each loan category, arranged in descending order of importance in the aggregate portfolio. Columns 1 and 2 report Aggregate Level statistics, whereby outstanding loans are summed across all banks before averages are computed. Column 1 reports the percentage share of the aggregate loan portfolio represented by each loan type (Ratio). Column 2 reports the aggregate non-performing loan ratio (NPL) in each loan category. Columns 3-8 report bank-level results. Specifically, table values in Column 3 are the loan type percentage when variables are first computed at the bank-level and then averaged across all banks. Columns 4-8 report descriptive bank-level statistics for each loan type, expressed in millions of dollars.

	Aggregate Level		Bank Level					
Loan type	Ratio	NPL	Ratio	Mean	SD	P25	P50	P75
RES	33.90%	5.43%	31.76%	292.39	5401.7	7.98	22.45	59.54
C&I	18.67%	2.09%	13.82%	163.64	3065.3	3.01	8.82	24.47
NRES	13.32%	2.38%	22.16%	117.06	1138.6	4.02	16.6	53.33
CONOTH	8.73%	2.78%	7.54%	75.81	1473.6	1.39	3.5	8.51
CRCD	6.96%	3.96%	0.55%	62.36	1812.1	0	0	0
CONSTRUCTION	5.00%	6.19%	7.36%	42.59	437.3	0.62	3.82	15.86
OTHER	4.05%	1.79%	0.57%	37.75	1248.7	0	0.04	0.27
RESMULT	2.92%	1.72%	2.44%	25.9	476.9	0	0.79	4.58
LEASE	1.97%	1.48%	0.41%	16.06	351.9	0	0	0
INSTITUTION	1.79%	0.13%	0.12%	14.92	593.8	0	0	0
AGRICULTURAL	0.88%	1.53%	6.97%	7.65	73.2	0	0.54	4.66
FARMLAND	0.88%	2.10%	6.30%	7.79	43.2	0	1.39	6.08
FOREIGN	0.85%	3.09%	0.01%	7.46	521.9	0	0	0
SOVEREIGN	0.08%	1.40%	0.00%	0.65	33.7	0	0	0

Appendix V. Descriptive Statistics for of Main Bank Failure Predictors

This appendix presents descriptive statistics for various bank failure predictors used in our paper. The primary predictor of interest is the equity-to-loan-portfolio-risk (*ELPR*) variable, introduced in this study. *ELPR* is the ratio of a bank's shareholders' equity minus intangible assets, all divided by its loan-portfolio-risk (*LPR*), expressed in logarithmic form. For this purpose, *LPR* is the expected dollar loss due to default for a bank's loan portfolio, as described in Section 1. The predictive power of *ELPR* is compared to the following CAMELS indicators commonly used by regulators to monitor banks.

CAMELS proxy	**Definition**
C(capital adequacy)	Also referred to as *T1CR*, this variable is computed by dividing Tier 1 (Core) capital by a bank's risk-weighted assets (RWA).
A(asset quality)	Total non-performing loans and leases, scaled by each bank's total loans and leases.
M(management experience) & E(earnings)	DeYoung (1998) report that regulatory scoring of management quality and earnings ability is highly correlated with each bank's return on assets (ROA), measured as the ratio of net income after taxes and extraordinary items (annualized) to average total assets.
L(Liquidity)	The ratio of cash holdings to total deposit.
S(sensitivity to interest rates)	Net short-term assets as a percentage of total assets; computed as the difference between short-term assets and short-term liabilities, all divided by total assets.

	Mean	SD	P1	P5	P25	P50	P75
LPR (in thousands)	5922	17694	40	109	481	1386	3812
ELPR	2.3928	0.7178	1.0841	1.4180	1.8751	2.2806	2.8036
T1CR	0.1720	0.1051	0.0763	0.0931	0.1142	0.1419	0.1894
A	0.0288	0.0285	0.0000	0.0005	0.0092	0.0204	0.0387
M&E	0.0076	0.0110	-0.0453	-0.0113	0.0047	0.0089	0.0128
L	0.0840	0.0846	0.0095	0.0183	0.0343	0.0546	0.0994
S	0.0844	0.1719	-0.2774	-0.1662	-0.0233	0.0664	0.1778

Appendix VI. The failure of Silver State Bank

Silver State Bank (SSB) was a Nevada commercial bank with 17 branches in the Las Vegas and Phoenix metropolitan areas and loan operations across the western United States. On September 5, 2008, the bank couldn't meet the demands of depositors and was deemed insolvent by the state. The net cost to FDIC associated with the closing of Silver State Bank was estimated at between $450 million and $550 million.

Using a one-year forecast horizon, the *ELPR* value for this bank at the end of 2006 was 0.978. Based on the historical distribution of *ELPR* values at the end of 2006, SSB's *ELPR* is lower than the 1th percentile cutoff of 1.084. Therefore, *ELPR* would have flagged SSB as severely undercapitalized (with a probability of failing by Dec 2008 of 14.47%; much higher than the base rate of 2%). On the other hand, regulators using *T1CR* would have arrived at an opposite conclusion. The value of SSB's *T1CR* was 9.67%. According to the Prompt Corrective Action framework in place at the time, a *T1CR* ratio above 6.0% would place the bank in the "Well Capitalized' category. Therefore, *T1CR* would not identify SSB as a failure candidate in 2006.

The underlying cause of this bank's failure was its overexposure to risky real estate loans, especially mortgages on undeveloped land purchased for home construction (see table below). *T1CR* failed to consider the risk the bank faces from its highly concentrated holdings in these loan categories whose NPL rates are also highly correlated (historical pairwise correlation of 0.86). In contrast, *ELPR* took into account the imbalance in SSB's loan types, its high exposure to loan classes with high NPLs, and the high correlation between its loan holdings. Banks can remain profitable even as their loan portfolio risk increases. During the last quarter of 2007, Silver State's net income increased to $26.42 million from $22.51 million in the same quarter 2006. Other CAMELS indicators failed to pick up the mounting risk in this bank in part because of their reliance on profitability. Even as late as year-end 2007, bank regulators still regarded the SSB as well-capitalized.

Loan Composition of Silver State Bank in 2006

Loan Type	Dollar amounts in thousands	Proportion
CONSTRUCTION	**560,723**	**60.157%**
FARMLAND	8	0.001%
RES	28836	3.094%
RESMULT	7161	0.768%
NRES	**215,370**	**23.106%**
FOREIGN	0	0%
INSTITUTION	0	0%
AGRICULTURAL	0	0%
C&I	113,520	12.179%
CRCD	0	0%
CONOTH	4,505	0.483%
SOVEREIGN	0	0%
OTHER	1,551	0.166%
LEASE	411	0.044%
Total	932,085	100%

Appendix VII. Bank Holding Companies (BHC) Statistics by Year

Year	N of BHC	N of Banks held by BHCs	Average banks per BHC	Avg MCAP (in millions)	Avg ROE
2001	474	1032	2.18	1,605	11.04%
2002	472	970	2.06	1,443	11.83%
2003	474	951	2.01	1,522	11.72%
2004	473	923	1.95	1,561	11.03%
2005	475	914	1.92	1,505	11.02%
2006	463	862	1.86	1,658	10.22%
2007	467	870	1.86	1,346	7.85%
2008	451	795	1.76	1,099	-1.03%
2009	425	654	1.54	1,037	-5.50%
2010	412	593	1.44	1,153	0.07%
2011	404	558	1.38	1,092	2.95%
2012	392	512	1.31	1,322	6.48%
2013	394	504	1.28	1,641	7.63%
2014	369	464	1.26	1,863	7.75%
2015	360	442	1.23	1,941	7.86%
Average	434	736	1.67	1,453	6.73%

This table reports year-by-year statistics on bank holding companies. N of BHC represents the number of bank holding companies. N of Banks represents the number of FDIC-insured banks. Average number of banks within each BHC is defined as the number of banks divided by the number of BHCs. Avg MCAP represents the average market capitalization (measured in $ millions). Avg ROE represents the average return on equity. The bottom row reports corresponding values when annual results are averaged over the entire sample period.