STOCKHOLM SCHOOL OF ECONOMICS

Master Thesis in Finance
Spring 2014
Tutor: Assistant Professor Michael Halling

Enhancing the Swedish Deposit Insurance Fee

A Study of Bank Behavior, Fairness and Risk in a Simulation Setting

Niklas Martinsson★ and Fredrik Lindholm✚

ABSTRACT

The Swedish National Debt Office (Riksgälden) is considering altering the current Swedish deposit insurance fee model with the purpose of increasing fairness and risk-differentiation among participating institutions. This paper studies the current Swedish deposit insurance fee model in a U.S. data setting, drawing from more than 20 years of historical data between 1992 and 2013. It further considers a set of interesting variables, which could be used to enhance the model, focusing mainly on adequacy and the ambition to create good incentives. It uses extensive academic research, simulations of bank behavior, default costs and tests on relations of factors to bank failure in an assessment of three model specifications. The results indicate that some positive effects with respect to fairness and risk-differentiation of deposit insurance fees could potentially be obtained by expanding the current fee model in a relatively plain fashion, possibly making it simpler in the process of renewal.

Keywords: capital adequacy, bank regulation, bank risk, deposit insurance, risk pricing

We thank Daniel Barr and Ann-Christine Hagelin at Riksgälden for their input, aid and sharing of information. We especially want to thank our tutor Michael Halling, Assistant Professor at the Stockholm School of Economics and the University of Utah for his invaluable help and guidance, without which this thesis would never have been what it is.

Kindly send any correspondence to ★21802@student.hhs.se or ✚21577@student.hhs.se.

Table of Contents

List of Main Tables and Figures iv
Introduction 1
1 Background and Purpose 2
1.1 The Mission 2
1.2 The Swedish Banking System 3
1.3 The Deposit Insurance System in Sweden 4
1.4 Problems with the Current Swedish Fee Model 5
1.5 The Problem with Capital Ratios as Risk Differentiators 6
2 Research Questions 6
3 Related Literature 7
3.1 The Basel Accords and the Concepts of RWA and CAR 7
3.1.1 RWA and CAR in Banking Regulation 8
3.1.2 The Importance of Capital and the CAR 9
3.2 What Literature Says About Deposit Insurance 11
3.2.1 The Moral Hazard Problem 12
3.3 Pricing Deposit Insurance 12
3.3.1 Option Based Theory Pricing 15
3.3.2 Expected Loss Pricing 15
3.3.3 Key Ratio Based Pricing 16
3.3.4 Ratings Based Pricing 16
3.4 Pricing from Riksgälden's Perspective 18
3.5 Literature on the Parameters of Interest 19
3.5.1 Business Risk 19
3.5.2 Deposit Interest Rates 19
3.5.3 Diversification of Income and Assets/Loans 20
3.5.4 Balance Sheet/Loan Portfolio Growth Rate 21
4 Definitions of Parameters 22
4.1 Measure for Business Risk (BR) 22
4.2 Measure for Capital Adequacy (CAR) 23
4.3 Measure for Interest Rate on Deposits (DEPi) 23
4.4 Measures for Diversification of Income (DivI) and Loans (DivA) 23
4.5 Definition of Measure for Balance Sheet/Loan Growth (Lg) 23
5 Description of Data 24
5.1 The FDIC Data 24
5.2 Problematizing the Scientific Method 25

5.3 Why Use U.S. Data? 26
5.3.1 The U.S. Banking System – Important Considerations 27
6 Methods for Testing 30
6.1 Descriptive Method 30
6.2 Inferential Method 32
6.3 Modeling/Simulation Method 33
6.4 Backtracking Method 38
7 Results and Analysis from Testing 38
7.1 Descriptive Testing 38
7.2 Inferential Testing 43
7.3 The Current Swedish Fee Model Applied on the U.S. Banking System 47
7.4 The Simulation Model Run Using the Fee Models 48
7.5 Backtracking Default Banks 50
8 Summary and Conclusions 52
8.1 On Future Model Choice for Riksgälden 52
8.1.1 Simplicity 52
8.1.2 Fairness 52
8.2 Considerations 53
8.2.1 Suggestion – A Simple Multivariate Model 53
8.3 Connecting Back to the Research Questions 54
9 Discussion 56
9.2 What About the Fee Model for the Stability Fund? 56
10 Method Evaluation 57
References 58
Appendix 67
Reservations 67
Definitions of Capital 69
Swedish Fee Model Calculation 69
FDIC Data Files 72
Parameter Sources and Build 73
Banks in Sweden 77
Descriptive Testing Appendix 78
Inferential Testing Appendix 96
Empirical Fee Model Testing Appendix 112
Simulation Model Appendix 114
Backtracking Appendix 125

List of Main Tables and Figures

Tables

Table 6:1 Scheme – fee simulation models
Table 7:1:1 Summary table of descriptive testing
Table 7:2:1 Summary table of inferential testing, univariable
Table 7:2:2 Summary table of inferential testing, multivariable
Table 7:2:3 Summary table of inferential testing, reduced
Table 7:4:1 Summary table of scenario testing
Table 7:5:1 Table of results from backtracking testing
Table A1 Summary information on banks in Sweden, table 1
Table A2 Summary information on banks in Sweden, table 2
Table A3 Summary table of scenario testing
Table A4 Summary table of backtracking testing (15-year horizon)
Table A5 Summary table of backtracking testing (10- and 5-year horizons)
Table A6 Summary table of backtracking testing (3-year horizon)

Figures

Figure 6:1 Number of U.S. bank failures per year 1990-2013
Figure A1 Overview of links between FDIC data sets and parameters
Figure A2 Income composition 1992-2012
Figure A3 Loan composition 1992-2012
Figure A4 1992-2008 differences in CAR, 09-10 fails vs. total
Figure A5 Deposits 1992-2012
Figure A6 1992-2010 differences in DEPi, 09-10 fails vs. total
Figure A7 Comparison diffs 2001-2009, DivI & DivA
Figure A8 1992-2008 differences in DivI, 09-10 fails-total
Figure A9 1992-2008 differences in DivA, 09-10 fails-total
Figure A10 BR 2003-2008, total sample vs. 09-10 fails
Figure A11 BR 03-08 density, 09-10 fails vs. total
Figure A12 BR 1993-1998, total sample vs. 99-02 fails
Figure A13 BR 93-98 density, 99-02 fails vs. total
Figure A14 BR 1993-2008, total sample vs. 09-10 fails
Figure A15 BR 93-08 density, 09-10 fails vs. total
Figure A16 CAR 2008, total sample vs. 09-10 fails
Figure A17 CAR 2008 density, 09-10 fails vs. total
Figure A18 CAR 1998, total sample vs. 99-02 fails
Figure A19 CAR 1998 density, 99-02 fails vs. total
Figure A20 DEPi 2008, total sample vs. 09-10 fails
Figure A21 DEPi 2008 density, 09-10 fails vs. total
Figure A22 DEPi 1998, total sample vs. 99-02 fails
Figure A23 DEPi 1998 density, 99-02 fails vs. total
Figure A24 DivI 2008, total sample vs. 09-10 fails
Figure A25 DivI 2008 density, 09-10 fails vs. total
Figure A26 DivI 1998, total sample vs. 99-02 fails
Figure A27 DivI 1998 density, 99-02 fails vs. total
Figure A28 DivA 2008, total sample vs. 09-10 fails

Figure A29 DivA 2008 density, 09-10 fails vs. total
Figure A30 DivA 1998, total sample vs. 99-02 fails
Figure A31 DivA 1998 density, 99-02 fails vs. total
Figure A32 Lg 2003-2008, total sample vs. 09-10 fails
Figure A33 Lg 03-08 density, 09-10 fails vs. total
Figure A34 Lg 1993-1998, total sample vs. 99-02 fails
Figure A35 Lg 93-98 density, 99-02 fails vs. total
Figure A36 Lg 1993-2008, total sample vs. 09-10 fails
Figure A37 Lg 93-08 density, 09-10 fails vs. total
Figure A38 Annual fee payments and annual costs, per year (1993-2013)
Figure A39 Annual payments to running costs, net (1993-2013)
Figure A40 Yearly DIF net position (1993-2013)
Figure A41 Scheme test runs - SWE
Figure A42 Scheme test runs - ELP
Figure A43 Scheme test runs - UPD
Figure A44 Total DIF Net Comparison SWE-ELP-UPD
Figure A45 One-Year PD Transition 1993-2013
Figure A46 Five-Year PD Transition 1993-2008
Figure A47 Bracket LGDs

Introduction[1] [2]

Deposit insurance and bank stability systems enhance the durability of the relationship between banks and their clients. Deposit insurance schemes protect most savers and prevent bank runs because for all possible anticipated withdrawal policies of other agents with deposits in the bank, it does not pay to participate in a bank run when liquid assets are covered by the deposit insurance. With a deposit insurance system in place, public confidence in the banking and financial sector's stability is maintained. Additionally, deposit insurance allows banks to follow desirable asset liquidation policies separate from the cash-flow constraints imposed by withdrawals.

A troubled bank that faces a run on its deposits may have its existence questioned and stakeholders worried about an impending default. The bank may even fail as a result of the bank run as such (Diamond and Dybvig, 1983). In most countries today the banking system is one of the most significant pillars, making day-to-day activities work for both individuals and big corporations. As a foundation for sound future development of the world economy it is important to safeguard the stability of banks. Brought to light by the latest financial crisis was the immense pressure put on society as bank-client relationships wavered on a systemic level. Big banks were bailed out so as to prevent entire economies from collapsing.

Banking "safety net" systems differ across the world, with developed counties usually presenting superior systems compared to developing countries (Laeven, 2002). However, regardless of the level of sophistication, it still prompts the question of how to price it. With a world emerging from one of the biggest crises in modern times, the opportunity for regulators, banks and academia to come together and bring forward a new generation of stability systems is offered; systems that can play a significant role in how future crises commence, progress and resolve. This paper aims to contribute to the discussion on pricing of deposit insurance and to provide input into the development of the fee structure for the Swedish deposit insurance system.

Building on a thorough literature review on the topic of deposit insurance and comprehensive data, the thesis tests and assesses a few parameters of interest

[1] Section builds on Flaherty (2013)
[2] Section builds on FDIC (2000)

to quantify bank default risk. It also tests the performance of the current Swedish deposit insurance model over a 20-year period and provides two complementary models for setting the deposit insurance fee. Finally, bank risk behavior is tracked for a number of years leading up to the default event.

The study concludes that the current fee model essentially sets fees adequately across the population of banks but not between banks of different perceived risk. By employing an alternative pricing method, the fairness of fee setting is slightly improved. Focusing on expanding the current fee model with a set of parameters that show consistency over time and help mitigate moral hazard ought to be a favorable way forward for regulators. Nevertheless, the determinants of bank default risk are ample and this study works with only a small set of variables and models, pointing to the issue of determining what in fact is the optimal deposit insurance fee model.

1 Background and Purpose

This section introduces the topic of this paper and how it came about, provides a brief description of the Swedish banking and the deposit insurance systems and finally discusses around the major determinant and also issue with the fee model – capital adequacy.

1.1 The Mission

The *Swedish National Debt Office (Riksgäldskontoret, Riksgälden or RGK*) presented to us in September 2013 an idea of great interest but also complexity – to investigate how to reform and re-model the fee structure for the deposit insurance. Riksgälden is interested in finding out what fees banks should pay to the deposit insurance fund (DIF) and to what extent fees should vary among institutions.

As in other parts of the world, the deposit insurance represents an important part of the financial system in Sweden as it ensures the compensation of clients'[3] money placed with an affiliate bank, credit institution or a securities firm in the case of default. The government guarantees each depositor a reimbursement up to the amount of EUR 100,000 per institution[4]. Money is paid out only in the event of

[3] Individuals, businesses and other legal entities are entitled.
[4] Regardless of the number of accounts, applies to both capital and accrued interest, the EUR guarantee amount will be recalculated to SEK based on the daily average exchange rate the day on which the right to claim the guarantee comes into effect.

default or by specific order from *The Swedish Financial Services Authority (Finansinspektionen* or *FI*). To fund this system, connected banks pay an annual fee based on the total volume of deposits. The fee is somewhat risk-adjusted in the sense that banks considered riskier pay a higher fee than less risky banks. Today the single decisive factor for quantifying bank risk is the capital adequacy ratio (CAR). A government report in 2005 discussed different models for risk adjustment but this was before the onset of the 2007/2008 financial crisis (Heikensten and Alm, 2005). Since then, progress of this work has more or less halted. This paper aims to evaluate the current deposit insurance fee system, investigate a few parameters of interest for increased risk-differentiation and analyze how banks that subsequently fail behave in the time prior to default.

1.2 The Swedish Banking System

Sweden went through a serious banking crisis in the early 1990s, caused by an asset bubble after financial deregulation when lending ceilings and liquidity ratios were removed (Englund, 1999). Since then, banking in Sweden has developed significantly. The four major banks of today: Nordea, SEB[5], SHB[6] and Swedbank are financial groups with large but differently focused international businesses.[7] Next to the traditional bank functions, life insurance, money management and mortgages have all become more important as of late. International expansion focused largely on the Nordics and the Baltic states.[8]

The financial sector is important in the Swedish economy and employs some 100,000 people.[9] While Sweden had 117 banks in December 2012, the "big four" banks made up 75% of the market.[10] The four biggest banks have combined assets at four times Sweden's GDP (Magnusson, 2013).

Swedish banks are in good health compared to their peers in other countries. The recent financial crisis was weathered relatively well, with banks remaining profitable throughout. Banks showed significant resilience and strength after the crisis, with credit default swaps in 2013 suggesting SHB was Europe's safest bank. The top four banks' stocks all appreciated more than 15% in 2012, while the

[5] Short for Skandinaviska Enskilda Banken
[6] Short for Svenska Handelsbanken
[7] Swedish Bankers (Ref #1)
[8] Swedish Bankers (Ref #1)
[9] Swedish Bankers (Ref #2)
[10] Swedish Bankers (Ref #3)

Bloomberg 40 financial index expanded 8% (Magnusson, 2013) (see tables in appendix Banks in Sweden).

1.3 The Deposit Insurance System in Sweden

Madan and Unal (1998) mention that default can mean different things in different circumstances, but can generally be defined as a counterparty failing to deliver an agreed upon quid pro quo. The deposit insurance system in Sweden is activated in two cases: (1) when FI finds that a bank has failed to honor a contract with a depositor because of non-temporary financial issues or (2) when a bank is declared bankrupt.[11]

Before the 1980s, Swedish banking was heavily regulated. After a swift deregulation, Sweden introduced a deposit insurance fund temporarily in 1992. When the crisis passed, the responsible authority *Bankstödsnämnden* was removed and replaced by *Insättningsgarantinämnden*. A guarantee was again introduced in 1996 following a EU directive. Since 2008 Riksgälden is responsible for managing the deposit insurance. [12]

The task of Riksgälden is to act as the state's central financial authority[13]. Riksgälden is responsible for preventing serious disturbances to the Swedish financial system [14] and it is responsible for managing government loans and guarantees. Also, it is responsible for the calculation of fees for the deposit insurance and stability funds, as regulated by law.[15] [16] Recently Swedish authorities have expressed concerns that the current model for determining deposit insurance fees "has large shortcomings".[17] They are worried, among other things, that the model does not differentiate fees enough and that it is too dependent on one variable – the CAR.

The current system sets the fee based on the amount of deposits at a bank that is covered by the guarantee. A fee for every covered financial institution is calculated from a model based on a fixed base at 0.1 percent of total deposits and a variable risk factor of 0.6 to 1.4 depending on the relative fulfillment of capital

[11] Lag (1995:1571) om insättningsgaranti 1 Chapter 8 §
[12] Finanskriskomittén SOU 2013:6
[13] Finanskriskomittén SOU 2013:6 page 300
[14] Lag (2008:814) om statligt stöd till kreditinstitut, 1 Chapter 2 §
[15] Finanskriskomittén SOU 2013:6 page 300
[16] 1 kap 12 § Lag (1995:1571) om insättningsgaranti
[17] Regerinsrapport om Avgiftsmodell för Insättningsgarantin Dnr 2007-1600

requirements.[18] Relative fees are calculated based on capital adequacy, as defined in the Basel Accords. This means that banks with the lowest CAR fulfillment (highest perceived risk relative to other banks) will pay up to 0.14 percent, and those with the highest (lowest perceived risk relative to other banks) will contribute by paying 0.06 percent of the assessment base.

The deposit insurance fee that is charged to banks in any one year is based on the CAR and guaranteed deposits of the previous year. These are reported to Riksgälden by each institution.

Calculation of the fixed base in currency units:

$$fixed\ base = total\ guaranteed\ deposits * fee\ percent$$[19]

Calculation of the distribution value:

$$U(z) = a + bexp(-cz)$$

where z is the CAR value. See appendix Swedish Fee Model Calculation for further details.

1.4 Problems with the Current Swedish Fee Model

Riksgälden criticizes the fee model on multiple counts. Because the fee depends on a bank's relative capital adequacy fulfillment, it is fairly unpredictable. Banks can have their fees increased although they have improved their CARs. Also, the range is relatively small, so that being very risky does not result in large fee increases. The fee is based on a single ratio, which could be inherently flawed. Riksgälden wishes to explore the possibility to include other factors. Most importantly, the factors are required to, when included in a fee model, better explain the underlying business risk of the bank. Nygren and Hagelin (2007) comment that it would be interesting to study a select number of factors over a long time horizon.

Starting out with the purpose of testing, we have together with Riksgälden identified six parameters of interest: a coefficient of variation for net income as a proxy for business risk, the CAR, the interest rate paid on deposits, diversification of income activities, diversification of lending activities and the growth rate of the loan portfolio.

[18] 1 kap 12- 14 § Lag (1995:1571) om insättningsgaranti
[19] Current fee percent is 0.1.

1.5 The Problem with Capital Ratios as Risk Differentiators

Capital ratios are constructed from two components. The numerator is a measure of the capital of the bank, inversely related to the probability of failure. The denominator is a measure of the scale of the same bank. To assess capital adequacy, one needs to be able to quantify pure scale, i.e. bank size. It becomes important to accurately represent size, as this will affect the required level of capital. All things equal, larger and riskier banks need more capital to secure against the fluctuation of asset values. There are various approaches to the scale issue, where risk weighted assets is one of the most important in use (Estrella et al., 2002).

In theory, risk weighting should reflect the riskiness of banks better than simple ratios. However, problems arise since the process to actually risk-weight a bank's assets will at some stage require subjective judgment by the estimator. Because each loan is unique, it is difficult to evaluate its credit risk. Furthermore, banking is subject to other sources of risk than credit risk, such as interest rate risk and operational risk. Risk-weighting assets can weaken the relationship between capital ratios and these other risks (Estrella et al., 2002).

Nygren and Hagelin (2007) mention that capital ratios can be an imperfect measure of bank risk. Often, larger banks can afford having lower capitalization, because they have more stable revenue streams. Rating institutes have found that the correlation between high ratings and capital adequacy is negative. Estrella et al. (2002) find that banks rated AA+ or AA have, on average, a lower leverage ratio and gross revenue ratio than institutions rated between A and BB+. Banks that failed in the U.S. during the periods of 1989-1993 and 1984-1989 were not generally under-capitalized beforehand (Peek and Rosengren, 1997; Jones and Kuester King, 1995).

2 Research Questions

Looking critically upon capital adequacy as the single risk factor of the current fee model and thinking about the factors Riksgälden is interested in, the following three research questions are pursued as targets for the research of this paper.

1. Riksgälden criticizes the current Swedish deposit insurance fee model for being too reliant on capital adequacy as a measure of bank default risk. The regulators want to develop a fee system that better assesses different risks at different banks and ensures that fees are set fairly yet adequately.

We ask:

- Is the current deposit insurance fee model flawed?
- Is capital adequacy a good measure of bank risk on its own and in combination with other variables?
- Does it make sense to change the fee model?

2. Are the factors that Riksgälden is interested in important predictors of bank risk of default? Which, if any of these factors should be taken into consideration in a new fee model for the Swedish deposit insurance system to enhance risk-differentiation?
3. Using available data on the banking sector and the parameters of interest, what can we say about fairness in the distribution of fees and costs between banks over time? Can we detect any differences between failing and non-failing banks in terms of Riksgälden's factors?

3 Related Literature

This section presents the foundation for the research of this paper. It first goes through literature that is relevant for understanding the Swedish deposit insurance fee model of today. It continues with sections on deposit insurance in general, its pricing and different pricing mechanisms, also discussed in the perspective of Riksgälden. It finally goes through literature relevant for evaluating the parameters of interest.

3.1 The Basel Accords and the Concepts of RWA and CAR[20] [21]

The term risk-weighted assets (RWA) was brought to general attention by the Basel Accords; the first introduced being Basel I in 1988. As a result of the spectacular demise of the German *Bankhaus Herstatt* in 1974, the central bank governors of the G10[22] countries established the Basel Committee on Banking Supervision (BCBS) in 1974.[23] The BCBS does not issue binding regulation but acts as an informal board where policy solutions and standards are developed.

The Basel I standard aimed first to require that banks maintain enough capital to absorb losses without causing systemic problems and second to level the playing field internationally by removing competitive advantages enjoyed because of differences in regulation (Bank for International Settlements report, 1988). It

[20] This section mostly builds on Basel Committee on Banking Supervision (1988)
[21] This section also builds on Blundell & Atkinson (2010)
[22] G10 countries are Belgium, Canada, France, Germany, Italy, Japan, Netherlands, Sweden, Switzerland, the United Kingdom and the United States (actually 11 members)
[23] Bank of International Settlements http://www.bis.org/bcbs/history.pdf , page 1/8

required banks to hold a minimum CAR of 4% for Tier 1 capital and 8% for Tier 1 and Tier 2 capital combined. Basel I was succeeded by Basel II, introduced in 2004. Basel II suffered from a long implementation process, not sped up until the onset of the 2007/2008 financial crisis and never really came into proper effect in many jurisdictions, though effective in Sweden by 2007 (Finansinspektionen report, 2013). Instead, soon thereafter in 2010/2011, a third framework, Basel III was issued. This framework had been developed with the recent financial crisis in mind. The crisis had revealed deficiencies in financial regulation that neither Basel I nor Basel II seemed to cover. Initially Basel III was set for implementation over the period 2013-2015 but the process will most likely take until 2018 or 2019 before reaching a fairly global completion.

3.1.1 RWA and CAR in Banking Regulation

The idea of RWA is a fundamental keystone in the Basel Accords. The term means that the assets on a bank's balance sheet are weighted according to perceived risk with respect to their liquidity and in most cases the counterparty of the arrangement. Under Basel I, assets are weighted at five levels depending on their perceived credit risk[24]. Cash or governmental lending is perceived to be virtually riskless, so their risk weights would be 0% (i.e. they will not be included in RWA). On the contrary, lending to the public sector will get risk weights of 20-50%. Residential mortgages and lending to the private sector is seen to entail the highest risk, so risk weights would amount to at least 50% and perhaps 100% when calculating RWA (Le Leslé and Avramova, 2012; Sarma, 2007).

Under Basel II, what weights to assign depends in the aggregate on whether the bank has adopted the standardized approach (SA) or the internal ratings based approach (of which two versions are available: foundation- or F-IRB and advanced- or A-IRB) (Sarma, 2007). Besides getting approval by the national regulatory agency, only banks that meet certain minimum conditions and disclosure requirements are allowed to use IRB. The IRB approach builds on six main parameters and involves estimating four (M = maturity and C = credit amount are given) of them: PD (probability of default), LGD (loss given default), EAD (exposure at default) and default correlations for each credit exposure (F-IRB banks are only allowed to calculate PD). These parameters are estimated at the discretion of banks using their

[24] The risk-weights are 0, 10, 20, 50 and 100 per cent.

internally developed risk models. Basel III builds on the same approach for estimating RWA but imposes more stringent capital requirements.[25]

After going through the procedure of estimating RWA for each exposure (or exposure class), aggregate RWA are computed and used to determine the capital requirement for the financial institution (Sarma, 2007). Banks need to maintain at least 8% of RWA in the numerator for both Tier 1 and Tier 2 capital [26]in order to be "adequately capitalized". The reasoning being that the more capital the banks hold, the more resilient they are against shocks that alter the value of their underlying asset bases.

$$CAR = \frac{Tier\ 1\ (core)\ capital + Tier\ 2\ (supplementary)\ capital}{RWA}$$

An additional capital element was added in response to adding market risk (MR) as a component in a 1996 amendment to Basel I. Similarly to credit risk (CR), the market risk component can be estimated under Basel II via either the standardized approach or the IRB approach. Basel II also takes into account operational risk (OR) (Sarma, 2007).

$$CAR = \frac{Tier\ 1\ capital + Tier\ 2\ capital + other\ eligible\ capital}{RWA(CR) + RWA(MR) + RWA(OR)}$$

3.1.2 The Importance of Capital and the CAR

The CAR as a central affecter on banks' cost of capital is emphasized by Chami and Cosimano (2003) who state that the increased importance of equity leads to a raise of the CoC, concluding that this cannot be efficient. Banks would require a higher risk-adjusted rate of return on their assets, which in turn could have the effect of inhibiting economic activity. According to the authors, the cause would be regulators' attempt to force banks to choose a D/E ratio outside their optimum. By enforcing certain risk weights on assets, the regulator can affect the CAR in the same way as it could do by changing regulatory capital.

Contrary to this view, Acharya et al. (2011) argue that as bank leverage decreases the banks' equity stakes ought to become less risky, implying a lower CoC overall. Even if some loss of ROE will accrue due to deleveraging and bigger share of

[25] Bank for International Settlements (2005)
[26] Please refer to the Definitions of Capital appendix for details regarding the contents of capital.

equity, which in general demands a higher rate of return, equity investors will in the end demand a lower required return. Higher bank capital improves the incentives of banks to monitor their own borrowers and develop stronger long-term relationships and this, in turn, generates economic value. Mehran and Thakor (2011) suggest that bank capital and bank value are positively correlated. Banks with higher equity capital tend to generate higher value for shareholders in terms of NPV, fetch higher prices in mergers and carry higher enterprise values.

A similar case is made by Admati et al. (2010), who refute the idea that "equity is expensive" and that capital requirements are costly and would affect credit markets adversely. Instead, the authors arrive at the conclusion that better capitalized banks suffer fewer distortions in lending decisions and would perform better overall, making way for a higher level of regulatory capital being adapted.

Le Leslé and Avramova (2012) conclude that retaining risk-sensitive capital ratios is very important, especially in the aftermath of the recent global financial crisis. They also point out that the RWA approach of today may not be the optimal way to go forward. Confidence in RWA is declining and academic focus on the subject is limited. RWA estimations seem to differ widely among banks but there is no convergence in views about the materiality and relative importance of these differences and no consensus on policy implications. The study suggests that due to some key concerns, regulators may override banks' internal models and impose minimum risk weight floors.

Das and Sy (2012) say that a key concern about current methods of determining RWA is that they leave room for individual banks to "optimize" capital requirements by underestimating their risks and thus being permitted to lower their RWA, artificially increasing their CAR. Studying whether or not markets price bank risk as measured by RWA, they find that banks with higher RWA performed worse during the severe phase of the financial crisis, suggesting that equity investors did look at RWA as a determinant of banks' stock returns in this period. The asymmetry of information between banks, supervisors and market participants regarding how risky RWA are can lead to increased uncertainty about the adequacy of bank capital, which during a financial crisis can have damaging effects for financial stability. Haldane (2012) argues that the increased complexity of regulation is not only costly and cumbersome; it is actually suboptimal for crisis control. A report by the German Berenberg Bank (2013) promotes the idea that bank regulation has lost sight of the

purpose of capital and that regulators are blinded by the sophisticated mathematics and modeling involved.

3.2 What Literature Says About Deposit Insurance

A major disruption in the banking sector, such as a bank run or the failure of a systemically important[27] bank can have serious repercussions for the economy if it disables industry and private capital to take part in transactions. The first come - first served rule and information externalities make it rational for depositors who believe there might be a bank run to get their money out sooner than later (Chen, 1999). This can lead bank runs to become self-fulfilling prophecies that can force illiquid but nonetheless solvent banks into bankruptcy (Barth et al., 2004).

Deposit insurance systems are in place as part of the defense system against such events. The insurance saves depositors from the costs of monitoring banks themselves (Merton, 1977). Ennis and Keister (2010) mention that in the U.S., bank runs remained regular until the introduction of a national government-sponsored insurance system in 1933. More recent large-scale bank runs happened in Ecuador (1999), Argentina (2001) and Russia (2004). Even countries that have no insurance system in place will often face calls to help depositors in a crisis (Demirgüç-Kunt et al., 2008).

Today the practice of insuring the accounts of depositors is more widespread. After the adoption of a national deposit insurance system in the U.S., other countries adopted explicit systems slowly for the first 30 years, with only six being established. In 1995 49 countries had an explicit deposit insurance system. In 2003 87 countries did (Barth et al., 2004). Besides the increasing number of countries, coverage limits have been increasing over time.

There are of course dangers related to an insurance system. According to Calomiris (1990) an ill-conceived insurance system might increase the risk in the banking system rather than act as a stabilizer. A too generous insurance may make big investors less incentivized to exert market discipline on banks and banks consequently can become more prone to employ risk-seeking behavior, so-called moral hazard (Demirgüç-Kunt and Huizinga, 1999).

[27] A systemically important banking institution is defined as one whose disorderly failure would cause widespread disruptions in financial markets that could not easily be contained (Labonte, 2013).

3.2.1 The Moral Hazard Problem

A governmentally funded deposit insurance can offer protection, but does so at the cost of moral hazard[28]. The insurance can be viewed as a put option with a strike price equal to the pre-fixed value of debt (Merton, 1977). Therefore, if the banks do not pay more when they take more risk, they can increase the value of the put option (the insurance). This could involve decreasing capital-to-assets ratios or obtaining riskier assets. When banks do their planning, they ignore losses to the assets of guaranteed creditors and external effects on society.

Acharya et al. (2010) propose that regulators should focus on the externalities that failing banks impose on others in the form of costs due to insured creditors and possible bailouts, and undercapitalization spillovers to the economy.

Because they are insured against losses, depositors have less incentives to monitor the banks. They are likely to care less about the risks banks take. High personal returns become more important. The benefits of having a strong reputation are removed and banks are no longer rewarded for being safe to the same extent.

To avoid moral hazard, deposit insurance premiums should be risk-adjusted and a practice of early intervention and prompt action should be applied to weak and problem banks. The coverage limit should be low enough to encourage large depositors to monitor the banks and exercise market discipline. Limits on the insurance coverage expose some depositors to the risk of loss in the event of bank failure and provide incentives for demanding higher deposit rates from weaker banks or for withholding funds entirely from troubled banks. Excluding certain types of deposits for instance inter-bank deposits, government deposits or foreign-currency deposits can also achieve market discipline (Laeven, 2002).

3.3 Pricing Deposit Insurance

Deposit insurance systems can be funded or non-funded and contributions can be made before (e.g. into a deposit insurance fund) or after bankruptcy situations. Deposit insurance systems can also be compulsory or voluntarily. To reduce adverse selection, membership should be compulsory (Laeven 2002).

---

[28] Duan and Yu (1994) find that Taiwanese deposit-taking institutions were subsidized by the deposit insurance fund of Taiwan in 1985-1992. Fries et al. (1993) find that Japanese institutions were heavily subsidized by the deposit insurer during 1975 to 1992. Hovakimian and Kane (2000) find that U.S. banks shifted risk onto the safety net during 1985 to 1994.

Laeven (2002b) discusses the pricing of deposit insurance systems and distinguishes between two adaptations of insurance schemes. Countries may employ explicit deposit insurance, where the government needs to make clear several things, such as what accounts to insure and up to what amounts, which banks that should participate in the scheme etc. On the other hand, a country may elect to not mention any deposit insurance outright, in which case it is said to employ implicit deposit insurance. The gain for banks in either case is dependent on the effectiveness of the government to manage risk shifting. The opportunity-cost value of deposit insurance is higher in explicit systems and the value is higher for banks with concentrated ownership structures. This effect is offset in countries with higher quality and well-enforced legal systems.

Looking at explicit deposit insurance systems, the insurance is said to be underpriced whenever the insurer charges less than the estimated opportunity-cost value for the services it provides and vice versa. An underpriced insurance system indicates that the participants extract subsidies from it.

Explicit systems expand risk shifting in poor contracting environments (Demirgüç-Kunt and Kane, 2002) but this can be reduced by the imposition of loss-sharing rules, risk-sensitive premiums and coverage limits. Hovakimian, Kane and Laeven (2003) investigate how effective private and governmental controls are at mitigating bank risk shifting across a sample of countries. They find that large portions of variation in the effectiveness of risk control differ with respect to contracting environments.

Laeven (2002) continues to say that explicit deposit insurance regimes appeal to policymakers due to their ability to clearly "set the rules of the game" with respect to what applies to whom and when. Also, an explicit scheme protects small depositors without any immediate impact on the government budget.

It is important to price the deposit insurance system as efficiently as possible. This means that prices should be set in such a way that they reflect the risk shifted to the deposit insurer. Because depositors are many and the majority holds only a small amount of the total, their costs for monitoring is high (Laeven, 2002). Banks are opaque and difficult to understand (Le Leslé and Avramova, 2012). Supervision in such an environment can serve a socially positive role.

When discussing the issue of pricing deposit insurance, we must understand the nature of costs incurred by the insurer. When a guarantee is activated, all

deposits are to be covered up to the legal limits. But the bank must contribute to the extent of its ability. Therefore, the monetary contribution of the deposit insurance system is equal to the difference between what the bank can supply and the size of accrued guaranteed claims of depositors (Madan and Unal, 1998).

Central to the pricing of deposit insurance is the method to estimate the riskiness of a bank's assets. To estimate this risk the regulator can use a combination of qualitative (bank examinations on- and off-site) and quantitative indicators (such as CAMELS) (Laeven, 2002). Early models of risk of default often follow Merton (1974), explaining the risk of default with the volatility in value of a firm's assets. While this approach has had its share of success in explaining risk qualitatively, it has been less successful in practical application. Problems are related to modeling boundary conditions, like when default occurs and the division of resources amongst claimants (Duffee, 1999).

Literature points to the prevalence of market-based indicators, like *option-pricing models* (Merton, 1977). Such models are attractive since they are based on a theoretical framework that directly links the value of the deposit insurance contract to the value of the bank's assets and uses market values of equity and assets rather than accounting values.

In countries with developed capital markets, market-based models are preferred. Still, their application is limited since they can produce poor estimates of bank risk in countries with underdeveloped/illiquid capital markets and the fact that market information is not available for many of the banks.

An alternative approach is *expected loss pricing (ELP)*. This method builds on expected default probabilities of banks, which can be estimated through either fundamental analysis, market analysis (interest rates or yields of uninsured bank debt) or both.

Contributions can differ from the "actuarially fair price" of deposit insurance for various reasons. For instance, over- or underpricing may occur if the fair price estimate of the deposit insurance is biased. Also, the government may contribute funds or issue guarantees only for some deposits. Contributions may not be naturally smoothed over time. This can be the case when a deposit insurance fund reaches its target level, after which contributions are allowed to decrease or when contributions are set higher initially in order to quickly build up a minimum fund level.

3.3.1 Option Based Theory Pricing

Option based theories provide default probabilities from market data such as share price and volatility (Nygren and Hagelin, 2007). A simple model of this type would be the Merton model, with a simple bivariate outcome, an option either defaulting or not at time T. Ronn and Verma (1986), for example, argue that by using relationships between equity prices and call options on the one hand and insurance and put options on the other, it is possible to empirically calculate the insurance premium for FDIC deposit insurance. They suggest a premium related to the volatility of the value of assets. Other important models are provided by Longstaff and Schwartz (1995) and Madan and Unal (1998).

Option-pricing methodology is only feasible for banks that have observable market values of equity. Additionally, this kind of model is not very exact (Madan and Unal, 1998). However, Cooperstein, Pennacchi and Redburn (1995) illustrate how a bank's net worth can be estimated from reported cash flows so that deposit insurance valuation in principle can be applied even to non-traded banks. Nevertheless, the authors believe one should acknowledge the limitations of the option-pricing methodology, in particular when applied to banks in countries that are not market oriented.

3.3.2 Expected Loss Pricing

Laeven (2002) mentions that expected loss pricing has become more popular over time. It centered on a straightforward conceptual approach under which banks pay fees according to the expected future costs they will cause to the DIF. It is argued that an ELP system would, among other things reflect differences in risk between banks and generate enough revenues for the DIF to cover outflows. The logic is simple – let each bank pay deposit insurance fees according to its expected default costs and the fund should balance in the long run. This would ensure that the DIF is essentially self-financing. Lacking viable market data on nonpublic banks, the ELP approach is more convenient to use than the option-pricing approach.

The principle of ELP can be expressed by the three parameters PD, LGD and EAD (preferably insured deposits), which are related accordingly:

$$Expected\ loss\ (EL)_i = PD_i * LGD_i * EAD_i$$

Following this formula, default probabilities and loss given default estimates could feasibly be estimated using historical data. The level of insured deposits can readily be observed at any point in time. Values can be projected into the future in order to create a forward-looking EL measure. A proposed pricing structure suggests that expected loss is calculated via a "bottom-up" approach at the level of individual banks (Federal Deposit Insurance Corporation report, 2000).

3.3.3 Key Ratio Based Pricing

Another alternative is key ratio based models. These rely on accounting data and measure riskiness by using one or several key ratios to produce a "grade" (e.g. good/adequate/insufficient) for the institution. The current deposit insurance model is of this type. It uses the CAR as the only key ratio for assessing the relative riskiness of a bank (Nygren and Hagelin, 2007). These models often focus on finding early warning signals in balance sheet information to predict later problems (Bongini et al., 2002). Estrella et al. (2002) find that capital ratios tested on U.S. data for 1988-1993 are very good predictors of bank failure. Simple ratios are about as strong as more complex ones and can be applied at low cost. Demirgüç-Kunt (1989) provides a review interesting of key-ratio based models in his overview of the subject and Gonzales-Hermosillo (1999) provides a more recent study of factors ex-ante determining banking distress.

3.3.4 Ratings Based Pricing

Credit ratings are opinions about the creditworthiness of an entity. In theory, ratings based measures encompass many aspects of risk. Therefore, they can be quite comprehensive (Estrella et al., 2002). Credit ratings often include hard data and the assessment of a ratings committee. They are seen as reflecting relative creditworthiness compared to other entities (Packer and Tarashev, 2011). Rating agencies often publish studies relating historical association of credit ratings to default rates. This specifies how credit ratings work as indicators of absolute creditworthiness (ibid.). An advantage specific to some external ratings is that banks do not know on which precise parameters they are based, making it harder to game them and leaving less room for moral hazard (Estrella et al., 2002). However, this also leads to a lack of transparency. Credit ratings express creditworthiness (the opposite of default risk) on an ordinal scale. This scale is easy to understand and has the advantage that it can be tested against a large database of similarly rated entities

and their historical performance. Though, ratings often differ between agencies. In an overview of 70 banks by the BIS, only in 8% of cases did banks receive equivalent ratings from all agencies (Packer and Tarashev, 2011).

3.3.4.1 About Bank Credit Ratings

Ratings exist both as stand-alone and all-in, reflecting the intrinsic strength of a bank and its strength with external support. This is extra important in the case of banks, where external support has played an important role. The all-in ratings are more interesting to trading partners, while the stand-alone matter more to authorities, who might have to aid the bank at some point.

Bank ratings are also meant to account for systemic risk. This risk is hard both to define and to find a proper measure for (Packer and Tarashev, 2011).

3.3.4.2 Credit Ratings Today

After the recent financial crisis, the major rating agencies came under scrutiny for several reasons. Particularly they failed to highlight important risks, which parties that were exposed to these risks and the value of government support. The same had been true for previous crises, like the Asian crisis of 1996-1998 (Ferri et al., 1999). The bank failures led the major rating agencies to reconsider their strategies (Packer and Tarashev, 2011). All major rating agencies are of the opinion that the creditworthiness of major European and American banks has deteriorated since before the crisis and they are in more agreement about creditworthiness than before the crisis, in part reflecting a greater faith in government assistance. Revisions to methodology combined with tougher rules and weak balance sheets are likely to lead to more downgrades.

For a sample of 60 large banks, 2007 credit ratings had a weak positive explanatory power of reliance on emergency measures. Pre-crisis credit default swaps, an option theory type indicator, had a weak and *negative* predictive power on crisis performance. Financial key ratios, like Tier 1 capital ratios, proved useful. Banks with high such ratios needed little assistance, and vice versa (Packer and Tarashev, 2011).

Bongini et al. (2002) conduct a very interesting "horse-race" amongst market data option pricing, key ratios and credit ratings. They observe how well these can predict the performance of banks during the 1996-1998 Asian crisis. Both credit ratings and market data are found to lag real world effects and to overshoot in their

adaptation. Key ratios are found to have a relatively strong predictive power. Ratings add no power when controlling for balance sheet ratios. Credit rating changes are consistently late and are shown to take place after important crisis events. One main problem with credit ratings, which shows the weakest predictive power, is judged to be their strong correlation to country-specific factors. The "sovereign ceiling", whereby companies are never rated higher than their host nation that ratings agencies used to explicitly impose but now supposedly do not, makes comparisons in developing markets difficult. Borensztein et al. (2013) indicate that it is still relevant to understand ratings.

3.4 Pricing from Riksgälden's Perspective

In terms of Riksgälden's criteria, a big advantage of option based pricing models is that they provide an absolute measure of risk that is simple and that gives banks fair relative positions. A disadvantage is the volatility of the model type, as it is based on fast moving market data. Furthermore, concerns may be voiced about its limited applicability (market data) and the fact that it would give pro-cyclical results (Nygren and Hagelin, 2007). Lastly, the volatility of bank stocks has been higher than for other sectors for decades, making this kind of measure less reliable (Packer and Tarashev, 2011).

From Riksgälden's perspective, expected loss pricing offers an approach to setting fees that is both easy to use and that can be easily motivated. It provides a measure of absolute risk, which is attractive for determining risk-differentiating fees and for continuously quantifying amounts at risk (Nygren and Hagelin, 2007). Of course some fine-tuning will be required to estimate appropriate fees, but in a complex issue like pricing deposit insurance a simple and logical solution may be attractive.

For Riksgälden, key ratio carry advantages in that they are relatively simple and cost efficient to use. Adding more variables ought to improve risk differentiation. Disadvantages are the absence of a measure for absolute risk (expected loss/default magnitude) and that it, because of this, would be harder to calculate a fair fee. Another shortcoming is that qualitative variables cannot easily be included and may be omitted prematurely before their importance has been gauged. (Nygren and Hagelin, 2007).

There are advantages for Riksgälden to use ratings based models. These can include both quantitative and qualitative data and corresponding to a certain

expected loss they can produce an absolute measure of risk. They are, ideally, fixed over a cycle. The BIS finds that, while ratings in general are not procyclical, rating changes exhibit procyclicality to the business cycle (Amato and Furfine, 2003). The ratings are comparable with other external ratings. An issue would be the lack of publicly rated exposures. Currently, only seven of the financial institutions covered by the Swedish deposit insurance carry external credit ratings. (Nygren and Hagelin, 2007).

3.5 Literature on the Parameters of Interest

3.5.1 Business Risk

Business risk[29] signifies the possibility that a company will show lower profits than expected or that it will experience a loss rather than a profit. This risk is influenced by several factors, including sales volume, per-unit price, input costs, competition, overall economic climate and government regulation. It is indicated by research that higher business risk should entail a capital structure that has a lower debt ratio to ensure that the company can meet financial obligations at all times (Castanias, 1983; Kale et al., 1991).

3.5.2 Deposit Interest Rates

Martinez-Peria and Schmukler (2001) find that deposit rates are higher for riskier banks in Argentina, Brazil and Mexico. The depositors appear to "discipline" banks that take higher risks by demanding higher interest rates or withdrawing deposits. Peresetsky et al. (2007) similarly find that banks with riskier policies pay higher deposit interest rates in Russia. Kraft and Galac (2007), however, find that Croatian banks can use high interest rates to lure over depositors, whom they find to be "*relatively slow to link high deposit rates with increased portfolio risk*" (Kraft et al., 2007 page 329). A linkage between high deposit rates and portfolio risk was observed in Croatia.

Hellman et al. (2000) point out that if regulation focuses on capital adequacy and ignores deposit rates, then banks might have an incentive to increase deposit interest rates to gain funding for increasing asset risks. This would be especially true if banks focus on the short-term outcomes. Hanousek and Roland (2001) find that banks with low equity are more passive in liquidating bad loans. While they will try

[29] Business risk on Investopedia: Investopedia (Ref # 1)

to hide distress from regulatory authorities, such banks will use higher interest rates to attract depositors. Therefore, they theorize that high deposit interest rates may serve as an early warning signal of distress.

3.5.3 Diversification of Income and Assets/Loans

Diversification can mean having different streams of income, investing in different sorts of assets or using different types of securities as means of financing.

Some potential benefits of diversification are economies of scope, a better allocation of resources and the ability to use firm-specific resources in different spheres (Berger and Ofek, 1995).

Kwan and Laderman (1999) look at mergers and conclude that mergers that seek value from diversification in fact bring little value. They find some indication of the effects of different kinds of diversification: "*While real estate agency, title abstract activities, and real estate operation are more profitable than banking, real estate development may not be. Real estate activities are riskier than banking activities in general, and their diversification benefits for banking organizations are less clear."* Elsas et al. (2010) observe that bank profitability and valuation increase with diversification.

Altunbas et al. (2011) find that business models with high income diversification and strong deposit bases had significantly reduced bank risk during the 2007-2008 crisis. Lepetit et al. (2008) see European banks expanding into non-interest income activities have higher risks. However, this is mostly true for smaller banks and more trading is found to have a positive effect. Stiroh (2006) finds that some of the areas into which U.S. bank holding companies expanded were so risky that the increased volatility of these cash flows increased risk compared to less diversified banks. His findings *"show that investment banking, servicing, securitization income, gains from loan sales, gains other asset sales, and other noninterest income are particularly volatile activities."*

Stiroh and Rumble (2006) further examine whether the shift toward non-interest income generating activities has improved the performance of U.S. financial holding companies from 1997 to 2002. The authors find evidence that points to benefits of diversification but that these benefits are offset by the increased exposure to non-interest income-generating activities, as these are much more volatile but not adequately more profitable compared to interest-generating activities (lending). Within companies increases in revenue diversification is not

associated with better performance and increases in non-interest generating income activities produce lower risk-adjusted returns.

Looking at the functional diversification of banks, Baele et al. (2007) analyze panel data for 17 European countries between the years 1989-2004 and conclude that a higher share of non-interest sourced income out of total operating income increases banks' franchise values but that diversification also increases systemic risk while a nonlinear relationship is found between diversification and idiosyncratic risk. It seems as if what type of diversifying activities banks pursue matters more for their risk characteristics than the level of diversification itself. Research by Wagner (2010) supports the conclusions that while idiosyncratic risk can be marginally improved by diversification, the systemic risk will increase.

Mercieca et al. (2007) employ a sample of 755 small European banks for the period 1997-2003 to investigate whether the shift into non-interest income activities improves the performance of small credit institutions. The results show no direct benefits of diversification and an inverse relationship between non-interest income and bank performance.

Demsetz and Strahan (1997) find that large bank holding companies (BHCs) in general are more diversified than smaller banks. However, the increased diversification does not translate into a reduction in risk. Apparently there is a counter effect where the risk-reducing potential of large BHCs is offset by their relatively lower capital ratios and larger corporate and institutional client portfolios. Acharya et al. (2006) produce results of the same kind. Their investigation of data for 105 Italian banks between 1993-1999 shows that diversification does not guarantee better performance or greater safety for banks. Rather, high-risk bank diversification is found to reduce returns and increase the risk in loan portfolios. For low-risk banks, diversification provides an inefficient risk-return tradeoff or only marginal improvement.

3.5.4 Balance Sheet/Loan Portfolio Growth Rate

Köhler (2012) shows that banks with relatively high rates of loan growth are riskier than their peers. It is argued that banks lower their lending standards in order to capture more customers and undercut competitors. Moreover, banks that are eager to lend may attract customers with lower credit quality, ones that have been turned away by other banks. Foos et al. (2007) show that loan growth leads to a peak in loan loss provisions three years later, decreased relative interest income and lower

capital ratios. It also leads to lower risk-adjusted interest income. Laeven (2002a) uses a proxy for bank risk and shows that this proxy has predictive power in forecasting bank distress. He also finds that this measure of bank risk is higher for banks with high credit growth. A 2013 report by the German Berenberg Bank claims that growth is the most important driver of bank risk.

4 Definitions of Parameters

Having discussed a broad spectrum of literature both on banking regulation, deposit insurance, pricing and the risk factors of interest, this section goes on to present the formal definitions of the parameters as applied in the testing procedures. See appendix section Parameter Sources and Build for data-specific adaptations of each parameter.

4.1 Measure for Business Risk (BR)

The definition of business risk derives from that of Kale et al. (1991). Business risk is represented by the coefficient of variation of any bank *i*'s cash flow standard deviation to its cash flow.

$$BR_{i,t-n,t} = \frac{avg(StDev\ of\ cash\ flow)_{i,t-n,t}}{avg(cash\ flow)_{i,t-n,t}}$$

Where *t* is the end year of estimation and *n* is the number of years across which the estimation is run.

In our specification of business risk, the net income of a bank is used as a proxy for cash flow as cash flow data are not available. The reason for choosing net income as proxy is that banks do not have the same profit and loss structure as other firms in the sense that they do not tend to keep regular fixed amortizations and depreciations of material size. Also, interest rate related items are the dominant type on the bank P&L. This makes the use of EBITDA, which is often used to proxy for cash flow illogical and non-optimal. From the data available, we believe net income is a reasonable measure to use. Both net income and its standard deviation are estimated from historical bank data to form the adjusted BR measure.

$$BR(adj)_{i,t-n,t} = \frac{avg(StDev\ of\ net\ income)_{i,t-n,t}}{avg(net\ income)_{i,t-n,t}}$$

4.2 Measure for Capital Adequacy (CAR)

The CAR is calculated by taking the sum of Tier 1 and Tier 2 capital and dividing by collective risk-weighted assets for each bank *i* at time *t* according to the formal definition set by the Basel framework.

$$CAR_{i,t} = \frac{(Tier\ 1_{i,t} + Tier\ 2_{i,t})}{RWA_{i,t}}$$

4.3 Measure for Interest Rate on Deposits (DEPi)

The average interest rate paid on deposits held is approximated by the following formula for bank *i* at time *t*. Naturally interest rates vary depending on account types, where some accounts carry a relatively high interest rate while other accounts often pay no interest at all. Information of that detail is not available to us so a simple average is used as a proxy.

$$DEPi_{i,t} = \frac{interest\ expense_{i,t}}{deposits\ held_{i,t}}$$

4.4 Measures for Diversification of Income (DivI) and Loans (DivA)

We construct Herfindahl-Hirschmann Index (HHI) measures for each bank *i* at time *t*, one parameter for income and one for loans. HHI is defined as the sum of the squares of exposures as a fraction of total exposure under a given classification. These parameters are specified as follows.

$$DivI_{i,t} = \left(\frac{I1_i}{REV_i}\right)^2 + \left(\frac{I2_i}{REV_i}\right)^2 + \left(\frac{I3_i}{REV_i}\right)^2 + \left(\frac{I4_i}{REV_i}\right)^2 + \left(\frac{I5_i}{REV_i}\right)^2$$

$$DivA_{i,t} = \left(\frac{L1_i}{L\&L_i}\right)^2 + \left(\frac{L2_i}{L\&L_i}\right)^2 + \left(\frac{L3_i}{L\&L_i}\right)^2 + \left(\frac{L4_i}{L\&L_i}\right)^2 + \left(\frac{L5_i}{L\&L_i}\right)^2$$

Where *I* indicates income type, *L* indicates loan type, *REV* indicates total revenues and *L&L* indicates total loans and leases. These measures will vary between 0 and 1 for each bank. A lower value indicates more diversification and vice versa.

4.5 Definition of Measure for Balance Sheet/Loan Growth (Lg)

To estimate balance sheet growth for bank *i*, we use a simple geometric mean.

$$Lg_{portfolio\ i,t-n,t} = \sqrt[n]{(L_{i,t} - L_{i,t-n})} - 1$$

Where g is the average annual portfolio growth rate, n is the number of years over which loan growth is measured, L is the aggregate portfolio value at each point of observation and t is the end year.

It is suitable to use a geometric mean rather than an arithmetic mean since we are interested in the growth rate of the balance sheet over time rather than capturing annual fluctuations. A bank may rapidly increase and then decrease its asset base over a few years, leading the arithmetic mean to display disproportionate growth. In fact, in the end the bank in question may not have materially altered the size of its loan portfolio. Changes in the portfolio over time disregarding yearly fluctuations are better captured by the geometric mean.

5 Description of Data

This section introduces the data used as well as an evaluation of the premises for testing the data. Publicly available U.S. banking data are used, obtained from the FDIC website. The FDIC data are comprehensive and consist of a long range of quarterly observations comprising about 7,000-13,000 banks depending on the year of observation.

5.1 The FDIC Data

Through the FDIC website (www.fdic.gov) one can find the databases "*Bank Find*" and "*Institution Directory*". These databases allow users to locate FDIC insured banking institutions, look at financial reports of such institutions, compare banks and download predefined and standardized datasets. Among the datasets available for download are lists of institutions and their geographic locations, quarterly financial data for all FDIC insured institutions available in .zip file format and data on annual branch office deposits, also available in .zip. From the financial data section, .zip files are available from the quarter ending 1992-12-31 up until 2013-09-30 (at the time of writing). Each quarterly folder (named "*All_Reports_yyyymmdd.zip*") contains about 62 separate Excel workbooks with different financial data split by bank using the identifier "*cert*" (the unique number assigned by the FDIC and used to identify institutions issuing insurance certificates). Also available from the FDIC website is a "*Failed Banks List*" (a .csv file) where each banking institution that has defaulted since 1934 is listed. The "Failed Banks List" contains information about whether the failing bank was acquired by another bank

or not, how accounts and loans were affected and how claims against the receivership could be filed. Columns outlining the levels of total assets and deposits upon failure, expected costs to the FDIC and whether the transaction was an outright failure or assistance are included as well. This list will provide the default incidences for our testing.

We download data in .zip files described above for all quarters between 1992-09-30 and 2013-09-30 to form quarterly panel data of U.S. FDIC insured banking institutions.

From the data we extract workbooks containing asset and liability information and income and expense information. These are joined to form coherent sets following a chronological order. Workbooks that specifically list details regarding the deposits at institutions are also extracted for the same period and periodicity. These are joined to the assets and liability data to form the balance sheet data set. The other data set is separate and contains all income and expense data. Thus, we end up with two inclusive sets of data.

To conduct our study we create from the raw data, by various procedures, the parameters of interest. After this and the removal of erroneous or otherwise problematic observations the data sets are ready to use. See Appendix Parameter Sources and Build for a diagram that explains from which data sets our parameters are built and for details regarding parameter construction.

5.2 Problematizing the Scientific Method

As a scientific purpose, we want to establish how well the deposit insurance fee model currently employed by Riksgälden works over an extended period of time on a large set of data. As history has shown, Swedish bank default and related losses have been quite low. The Swedish bank market did not look as it does neither in structure nor regulation until after the 1991 crisis, which was the last time a major Swedish bank failed. It is of course problematic for testing that the deposit insurance fund has had to pay money on only a few occasions. In total, there have been three payments since the deposit insurance was introduced in 1996.[30] Adding to this, the

[30] Riksgälden (Ref # 1)

number of Swedish banks is small (abt. 117)[31] making it harder to obtain a good blend of sector participants.

It is hard to use Swedish data to any great length if we are interested in testing the efficiency of models in terms of pricing bank default risk. This ought to be best done on a larger sample, over a relatively long period of time and with relatively many incidences of default. This can be achieved by employing the U.S. data.

5.3 Why Use U.S. Data?

There are both advantages and disadvantages to using U.S. data for testing a fee model that should be applicable to the Swedish bank system. We provide an outline of the U.S. banking system and its similarities and differences to the Swedish banking system.

There are several benefits of using U.S. data. First of all, the relatively large number of banks observable over a considerably long period of time allows for better comparative studies and scenario testing compared to the scarce Swedish data. We can track individual banks for 20 years and form a good ground for obtaining solid test results. Second, the detailed level of the U.S. data allows us to perform various customized testing procedures. Third, the U.S. data contain many defaults. Having a larger quantity of defaults is preferred as the primary task for the model is to price default risk. Fourth, what happens in the U.S. financial market has and will likely continue to have an effect on the rest of the world. Therefore, we believe what is observed among U.S. banks in terms of risk and default will be of interest in a European/Swedish setting as well.

An important drawback of using the U.S. data is first and foremost the realization that the U.S. and Swedish bank systems are essentially two separate entities. Country specific characteristics will prohibit one-to-one comparisons. A particularly important consideration is the differences in regulation. In applying the Swedish models on the American data, inconsistencies due to regulatory differences will be produced and one must be careful to point this out.

[31] Swedish Bankers (Ref # 4)

5.3.1 The U.S. Banking System – Important Considerations[32]

Compared to the Swedish banking system, which is small, the U.S. has one of the largest banking systems in the world with banks having everything from nationwide and even worldwide operations to small operations on a state or county level.

Since the 1980s, the U.S. banking system has undergone several structural changes. One of the most notable transformations is the industry wide consolidation: in 1980 there were more than 14,000 banking institutions, a figure that is down to approximately 6,000 today. With this consolidation has also followed an asset concentration, with more and more assets belonging to a smaller group of banks [33]. The majority of changes that have taken place over recent decades can be ascribed to the changing regulatory environment, caused primarily by the increasing complexity of banking operations and the Savings and Loan crisis. Coming from the changes in this period was the ability of banks to achieve increased operating efficiency and profitability by changing their business models to focus on large transactions. This in turn led to cost savings due to economies of scale and bigger banks could grab hold of the market, acquiring or cannibalizing smaller competitors to obtain dominance.

Despite the consolidation trend, the banking industry is still highly dependent on smaller banks. Many new entrants have been smaller banks that cater to different demographics of customers compared to the larger institutions. They tend to earn income in a different manner than their larger counterparts, usually with a higher share of interest income. Although their size limits the geographic areas in which they operate, these smaller institutions can be vital to the communities they serve.

The coming decade may be one of transition for the banking industry as it tries to adjust to a new regulatory environment and continued low interest rates. In general, the banking industry's health is improving as deleveraging takes place. Competitively, the banking industry must engage customers in areas in which it provides important services such as payments and consumption-smoothing lending products. If the economy does not experience rapid growth, smaller banks can benefit because they perform these particular functions very well. In addition to

[32] Section builds on Flaherty (2013)

[33] The percentage of bank assets held by institutions with $10 billion or more in assets (adjusted for inflation) has increased from 46% in 1992 to 80% in 2012.

being at a disadvantage on these grounds, larger institutions should continue to face more regulatory scrutiny as international regulations are put to use.

Some similarities between the U.S. and Swedish banking sectors

- They have both seen increasing consolidation, both with respect to the number of players (four or five big banks) and to the assets held (with big banks holding more and more of aggregate assets).
- Both have seen increasing regulation and regulatory shifts taken place spurred by big crises in the late 80s and early 90s (the S&L crisis in the U.S., the real estate crisis in Sweden).
- Both banking systems have collective assets larger than their respective GDPs.
- The financial services industries are important pillars of society and employ a large workforce in both countries.
- Despite having applied different sets of regulatory frameworks earlier (the U.S. has stuck with Basel I combined with domestic regulation for the time since the 1980s while Sweden has been more active in adapting newer versions of the Basel Accords and conform to E.U. standards), today banking industries in both countries face the pressure of the latest wave of regulation (Basel III) which prompts banks to deleverage, increase regulatory capital and become more wary of what types of assets are "good" and what types are "bad" as implied by the new regulation.

Some differences between the U.S. and the Swedish banking sectors

- The sheer size difference both geographically and population-wise. In the U.S. banking can still be very much local with areas covered only by local/municipal actors. In Sweden, while a few such actors are available it is easy to notice the dominance of the big banks anywhere in the country.
- Regarding regulatory agencies, Sweden's banking industry is supervised by FI alone, with some specific administration (deposit insurance, stability funds) run by RGK on a national level. In the U.S. on the other hand, banking is regulated both on the federal and state level and is highly fragmented

compared to Sweden and the other G10 countries.[34] The U.S. maintains separate securities, commodities, insurance and bank regulatory agencies at both the federal and state level.

- The extent of application of new regulatory frameworks such as Basel III across institutions in the U.S will likely be a lot different than in Sweden. While many of the smaller institutions in the U.S. expect to be permitted to stand outside Basel III, this is not likely in Sweden.

5.3.1.1 Differences between definitions of capital in the U.S. and Sweden

Despite having kept the definitions of Tier 1 and Tier 2 capital relatively unchanged from Basel I, capital varies due to differences in national legislation and the mandates of the domestic supervisory authorities to tailor the capital according to each specific legal system. Even though there are similarities in regulation between both systems, the regulatory differences can make the CARs of U.S. banks to differ from the CARs of Swedish banks. This is important to notice since the current fee systems in both Sweden and the U.S. put a lot of weight on the CAR.

An important difference in the case of comparing bank capital levels in Sweden to those in the U.S. is that Sweden has used Basel II since February 2007 (Basel III from 2014), while the U.S. has used mainly Basel I with modifications. Sweden has also allowed its major banks to use the A-IRB approach to calculate credit risk components. This will affect the calculation of bank capital since, according to Swedish law; banks will need to partly adjust their capital levels based on the LGD parameter, which is estimated by the banks' internal models and therefore is a very bank-specific measure. For example, large Swedish financial institutions' average risk weight of mortgages using the A-IRB varies from 4.9% for SHB to 16.3% for Länsförsäkringar Bank, instead of 50% across under Basel I or 35% under the Swedish alternative method *Schablonmetoden* (Finanskriskomittén, 2013, page 30). When specifically permitted by Riksgälden, Swedish banks can use the A-IRB to calculate the capital base that is used for the fee model.[35] When banks are not permitted to use this method, they must use Schablonmetoden, which is more similar to U.S. equivalents.

[34] FRBSF (Ref # 1)

[35] Lag (2006:1371) om kapitaltäckning och stora exponeringar 4 Chapter 7 §

Keeping things in the aggregate, we are aware that bank capital definitions in Sweden and the U.S. differ but we believe it is possible to use the U.S. Tier 1 and Tier 2 capital bases as proxies for the Swedish equivalents when we conduct tests on U.S. data. A good aspect is that these ratios should be more conservative for the U.S. since older regulation gives considerably less leeway for banks to adjust risk-weights downwards (Bundesbank report, 2006). [36]

6 Methods for Testing

Above it has been explained what parameters are of interest to test, how they are constructed as well as what data will be used for testing. This section describes the testing procedures followed in this paper. First, the descriptive method is explained, followed by the inferential method, the modeling and simulation, and the backtracking methods respectively.

Our approach is the following: First we will empirically try to assess how good the set of interesting parameters (BR, CAR, DEPi, DivI, DivA and Lg) are at discerning and predicting banks that later go into default from the total population of insured banks. For this we use descriptive and inferential analyses. Second, we want to test how well the current Swedish fee model would have performed if it had been implemented in the U.S. over a 20-year period. We apply the Swedish fee model formula to historical U.S. banking data. Third, we move into a theoretical setting where we create a small universe of U.S. banks including their behavior, defaults and fee payments over time, drawing from 20 years of bank data. We build Excel simulation models; one representing the true Swedish fee model, an identical model that instead uses expected loss pricing and a model that uses additional parameters for calculating the fees. A comparative study is made between the different models. Finally, we backtrack default banks for time periods of varying length in order to discern patterns in their behavior.

6.1 Descriptive Method

We look at the FDIC data over the 20 years available from 1992 to 2013 and estimate values for each bank for the parameters as described in appendix section

[36] A 2006 study undertaken by the German Bundesbank found that implementing Basel II from Basel I led to an average 6.7% reduction in the capital requirements for German banks. It was even higher, however, for banks using IRB, and A-IRB. For A-IRB banks there was a reduction of 15.1%.

Parameter Sources and Build. In order to compare banks, we separate banks that subsequently default ("fail banks") from the total population of FDIC insured institutions ("total"). In this particular time period, bank defaults are clustered around a few crises: the late 80s/early 90s banking crisis, the burst of the dot-com bubble around the turn of the millennium and the major financial crisis of the late '00s. We choose to focus our observations around two out of these three – the 1999-2002 and 2009-2010 default sub periods. This decision is made in part because the frequencies of defaults are elevated and in part because by looking at separate crises of different origin hopefully will allow us to assess the persistence and accuracy of the parameters over time and draw some conclusions about their implied importance for future usage. As our time series data start at the end of 1992, we miss most of the late 80s/early 90s crisis period. Ideally, we would need data starting from the mid 80s to completely cover that crisis.

There is a big difference in the frequency of defaults between the years around the millennium crisis (30+) and the 2007/2008-crisis (300+) (fig. 6.1). A greater uncertainty arises for outcomes that are estimated using fewer defaults. Keeping this in mind we also realize that the number of defaults over the millennium crisis, while being considerably lower compared to the much bigger financial crises still is elevated considering the surrounding years.

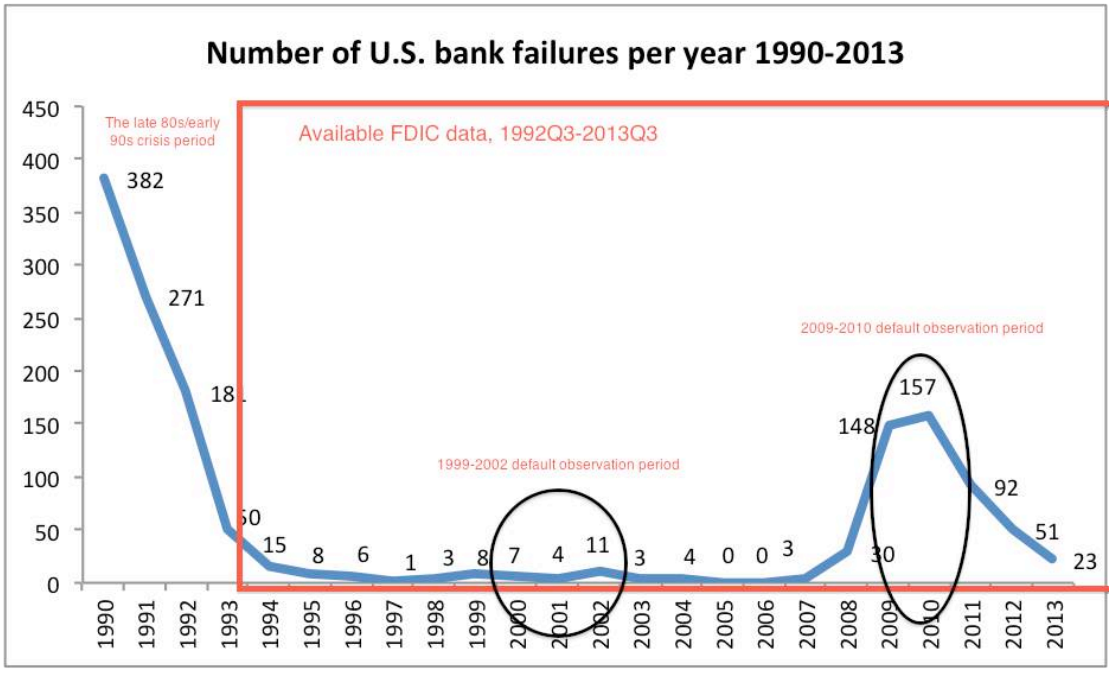


Figure 6:1. The figure displays the annual default frequencies of U.S. FDIC insured banking institutions between 1990 and 2013. The red box represents the time frame for available data and the black circles represent the crises periods used for testing in this paper. Source: The FDIC Failed Bank List.

6.2 Inferential Method[37]

In the inferential testing procedure, we focus on the same two crisis periods as above: 1999-2002 bank failures and a part of the latest financial crisis, 2009-2010 bank failures.

We estimate parameter values as described in appendix section Parameter Sources and Build for the tests on 1998 and 2008 data. For 1998 data we use the 1999-2002 default period as our dependent variable (24 viable observations[38] out of 30). For 2008 data we employ the 2009-2010 default period as our dependent variable (115 viable observations out of 304).

We collect all values for the 1998 and 2008 data in two separate .csv files and use the statistics software program STATA for inferential testing. Data are labeled and adjusted as needed. Following the notion in Pohlman and Leitner (2003), we apply a logistic regression model since the dependent variables are of binary nature with 0 or 1 indicating either survival or failure. The general specifications for one and multiple covariate models respectively are:

$$logit(\Pi) = log\left\{\frac{\Pi}{1-\Pi}\right\} = \alpha + \beta x$$

$$logit(\Pi) = log\left\{\frac{\Pi}{1-\Pi}\right\} = \alpha + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_k x_k$$

where Π is the probability of success (i.e. 1 or "fail") at covariate level x.

The logistic regression model can be rewritten as

$$\frac{\Pi}{1-\Pi} = e^{\alpha+\beta x} = e^{\alpha}\{e^{\beta}\}^{x}$$

where e^{β} represents the change in the odds of the outcome by increasing x by one unit, i.e. every one unit increase in x increases the odds by a factor of e^{β}.

$$\beta = 0\ (e^{\beta} = 1) \rightarrow \Pr(success)\ is\ the\ same\ at\ each\ level\ of\ x$$

[37] Procedure builds on:
Regressions (Ref # 5)
Regressions (Ref # 2)

[38] Viable observation – default observations for banks that have usable values on all parameters. Some banks for instance, had not been operating long enough for five-year averages to be applicable and so they were either missing both BR and Lg or these measures would have needed to be estimated differently. In other cases, missing data would result in incomplete estimation of one or several of the parameters. For ease of comparison, fairness and output stability, we have chosen to exclude banks that do not fulfill all six parameter values according to their original definitions.

$$\beta > 0 \left(e^{\beta} > 1\right) \rightarrow \Pr(success)\ increases\ as\ x\ increases$$

$$\beta < 0 \left(e^{\beta} < 1\right) \rightarrow \Pr(success)\ decreases\ as\ x\ increases$$

The further away from one an odds ratio is, the stronger the association (positive if >1, negative if <1).

We briefly describe the data set and then specify and run univariable logistic regressions for each parameter. We test for multicollinearity and correlation among parameters to make sure no material inter-variable relationships exist. In the next step we estimate multivariable logistic regressions including all and subsets of parameters to investigate if and how the degrees of explanation and significance differ. The final step is to test whether or not each multivariable specification passes the link test, a goodness-of-fit assessment, identify influential cases and test the assumption of linearity. See explanations of these tests and other details in the Inferential Testing Appendix.

6.3 Modeling/Simulation Method

Empirical testing

We apply the Swedish model to the population of U.S. FDIC insured banks over a period of 20 years between 1992 and 2012. For each bank, a fee in 000's USD is calculated at the end of each year according to the procedure described in section Swedish Fee Model Calculation. The test assumes payment of fees in the first quarter the year immediately after that for which the fees have been estimated (e.g. if payment occurs in Q1 2009, the fee covers 2009 and has been calculated using data as per Q4 2008). The collective fee amount from all FDIC banks is then compared to the actual annual costs to the DIF resulting from bank failures. DIF net positions per year and cumulative are calculated and accumulated DIF costs are compared to the accumulated fee payments on a yearly basis. This procedure will allow us to somewhat perceive how well the current Swedish fee model would have performed if it had been used in the U.S. and highlight both its strengths and weaknesses.

100% Swedish simulation model (SWE)

A simulation model for the U.S. banking system is created that applies the current Swedish fee model according to description. The reason for also constructing the model in a simulation setting is that we want to build flexibility into the system. We will then be able to change parameters and values as desired when we conduct tests.

The simulation is constructed around nine hypothetical U.S. banks that represent the broad spectrum of the nine brackets (based on the CARs) into which banks may be classified by the current fee model. We move from testing the fee model on the entire FDIC system empirically towards testing the model in a theoretical setting where we can decide what scenarios to run and when.

The simulation draws nine values of CARs, one for each bank. The draws come from nine matrixes of CAR observations from the years between 1993 and 2013. Each such matrix represents banks in a certain bracket. The draw is constructed so that first a single year between 1993 and 2013 is randomly identified, this will determine what column of each matrix one to nine a CAR value will be drawn from (vertical selection). Then, a row number is randomly selected, this will determine from what row from each matrix one to nine a CAR value will be taken (horizontal selection). These CARs are then used to calculate the Swedish fee amount as described in section Swedish Fee Model Calculation. One- and five-year transition matrixes are then employed to simulate where banks are likely to end up bracket-wise over a one and five year horizon respectively. Likewise, one- and five-year PD matrixes provide each bracket 1-9 with the likelihoods of default over hypothetical one- and five-year periods. In case of a bank default event, the default costs are estimated using the level of deposits and the LGD matrix. This cost will be put in relation to the fees paid by the bank and we can assess if the DIF ends with a surplus or deficit in the particular case.

Default costs and fees paid are calculated for each bracket and collected bracket by bracket. The nine brackets are treated as nine separate funds, which allow us to observe the balance of each bracket and whether banks in a specific bracket are supporting themselves (i.e. whether fees paid in to the fund by a bracket group of banks cover the default costs of banks that belong to that specific bracket).

The logic of applying a multiple fund system in the model is that it becomes easier to differentiate risk depending on bank brackets. If all nine brackets balance, the entire DIF also balances per se. It is attractive to evaluate fund performance on a bracket level since different brackets may need different amendments to their fee structures in order to even out.

Please refer to the Simulation Model Appendix for details regarding all simulation models.

ELP simulation model

Out of the pricing types we discuss in section 3.3 on the pricing of deposit insurance, credit rating and option pricing models both require information available from the market or external agencies and are not suitable to test in our limited setting. At the same time we realize that an expected loss pricing model should be fairly easy to apply given the existing data. We add to the 100% Swedish simulation model an expected loss pricing (ELP) function, where the only difference is the fee calculations. In the ELP case fees are calculated on a bracket level according to the formula described in section 3.3.2 – each bracket PD is multiplied by each bracket LGD and finally multiplied by each bracket level of deposits. DIF net positions are then derived on a per-bracket and fund level by subtracting default costs from fee income exactly as described above.

Updated simulation model (UPD)

We expand the 100% Swedish simulation model to include our variables of interest: business risk (BR), interest rate on deposits (DEPi), diversification of income (DivI), diversification of assets/loans (DivA) and loan growth (Lg), controlling for size. We calculate a fee based on all these inputs together with the CAR parameter. The fee is set so that each of the above values should contribute a certain amount on average, with a target fee total of the amount required to make the fees to equal expected expenditures. We have the ambition to construct the combined fee so that one fifth is to come from each of the 100% true Swedish fee (CAR-based), BR, Depi and Lg, and the last fifth from DivI and DivA combined.

For each simulation run, bank data are drawn at random from actual data for each bracket bank. For instance, for the one year transition matrix, data are drawn with a random, VLOOKUP function from an n = 7,121 rows data set of year 2008 observations of all the banks which have values for all used variables. Thus, if n= 7,000 is drawn for bracket 9 (which consists of banks 6,331 to 7,121) a row of the Swedish fee model, BR, Depi, DivI, DivA and Lg are constructed representing one actual bank: bank number 7,000. For each simulation run, a total of nine banks are drawn (one for each bracket) and a total "system" fee is calculated for these.

The fees coming from each variable are set based on the regression results of these variables and resized using a data table. By controlling in the data table the

average fees produced by different formulas, we are able to make the fees on average equally large by adding a constant to each fee formula.
Further, Lg is squared, so as to not allow it to take on negative values. We consider that negative loan growth should also be seen as a sign of instability, and not as anything positive. We then take the square root of the results to reduce variance. For the BR measure a floor is implemented in order to avoid too low values.

When it comes to default simulation and DIF costs, the model works in the same way as the original version.

LGD, PD and transition matrixes

LGD is estimated per bracket and based on 538 historical loss observations and estimations between 1996 and 2013. The final results are an average of three measures.

A bank is observed for five years to determine the average bracket over the time period preceding default. The reason for choosing a five-year time span as opposed to longer time spans used to look at fee payment, is that fee payment occurs over a long time, whereas losses are at a single point in time. For losses, the final period is most relevant, because the last observed capital ratios tell most about how much of a capital buffer there is for claimants to receive payments from. The less capital there is, the higher, theoretically, should losses given default be. However, since most banks are in the ninth bracket at the time of default, thus making other brackets lack observations and since we want to be able to use these LGD estimates not only to look at last year bracket results, we choose a five year period for our LGD estimates.

Next, we look at the basis of our three approaches. Thus, first, a bank in brackets 7,7,7,7,8 over the last five years would be assigned a bracket score of 7.2. These brackets will then be used to run a regression of observed LGD over average 5-year bracket score. The results show that average five-year bracket scores are a weak linear predictor of LGD: A logarithmic regression has slightly higher predictive value, but is still not very useful. It appears losses are high in the lower and upper brackets and are somewhat lower in the middle brackets.
Thus, as it does not seem useful to rely on regressions the three methods we use are the following:

(1) We extract average historical LGDs for all nine brackets, assigning each bank to a five-year bracket based on its average as calculated above. This gives us a

larger amount of observations for the lower brackets, and shows how five-year average scores correlate to loss given default.

(2) A calculation of LGD is done using modes instead of averages. This analysis assigns a loss to the bracket category based on the most frequent bracket in the five-year period.

(3) A five-year-ago bracket LGD is calculated. This simply places losses of banks in categories based on their brackets five years prior to default.

In this way, we get three different estimates of LGDs, out of which we take an average to create one aggregate LGD measure for each bracket.

The transition matrixes are estimated by tracking changes in banks' relative brackets on an annual and five-year basis. For instance, all banks observed in the last quarter of 2000 are placed in brackets. Then the 2001 brackets for these same banks are compared to the 2000 brackets and changes are observed. The changes are then mapped, so that the distribution of banks starting in for instance bracket 1 in 2000 is calculated for 2001. Accordingly, most banks that start off in bracket 1 will remain in the same bracket in the following year. However, a certain proportion will transition to bracket 2, and a smaller one to bracket 3, and so on for each bracket. This gives us the expected transition matrix. One- and five-year transition matrixes are calculated so as to see how banks move between brackets over varying time horizons.

PD matrixes are estimated similarly to transition matrixes by instead matching active banks in any year to banks on the failed bank list one year and five years afterwards respectively for the one- and five-year PD measures. If a bank is active in 2006 and is found on the fail list in 2007, it has defaulted over a one-year horizon while if it is found on the fail list in 2010, it has defaulted over a five-year horizon but not over a one-year horizon.

The simulation models are run according to the scheme specified below. The purpose of running several setups over different horizons is to test for model behavioral persistence and potential weaknesses. Ideally the models should be fair and adequate in their setting of fees regardless of the banks included or the macroeconomic state. See the Simulation Model Appendix for detailed outlines of the scenarios.

Scheme – Fee Simulation Models	Transition matrix	PD matrix
Average risk scenario	1- and 5-year average	1- and 5-year average
Minimum risk scenario	1- and 5-year minimum	1- and 5-year minimum
Maximum risk scenario	1- and 5-year maximum	1- and 5-year maximum

Table 6:1. The table displays the different test scenarios applied for the simulation model testing procedure. All simulation models are tested for each scenario and their output is stored for later comparison and evaluation.

6.4 Backtracking Method

We compute the cost distribution over different brackets for a set of time horizons. The idea is that only looking at the last year is very unfair because most banks have low capital levels when they fail. If we only looked at the last year, we would conclude that banks with low capital levels caused almost all the damage, and would only levy high fees on the banks that were momentarily low on capital. However, for the system to be fair, we should strive for each bank to cover its own costs over the long run. Therefore, we should look at bank contribution over longer time horizons.

We calculate costs for perspectives of 15, 10, 5 and 3 years to complement the 1-year horizon obtained by simply looking at the final bracket distribution of costs and fees. These sets are obtained by looking only at the banks that have failed and tracking past performance over these different time horizons. No longer sets than 15 years are used, mostly because the number of failed banks for which we have more than 15 years of data is limited.

7 Results and Analysis from Testing

This section presents the results from testing. Each testing method as described in section 6 is presented in turn. Analyzes complement the result presentations.

7.1 Descriptive Testing

Summary Table of Descriptive Testing						
	Failure Period					
Values	1999-2002		2009-2010			
Parameter	Fails	Total	Fails	Total		
BR	0.75	0.54	0.64	0.57	BR and Lg are estimated as five-year *annual* averages for 1993-1998 and 2003-2008 respectively. Other parameters are single observations at 1998 and 2008 respectively.	Long-term values for the parameters CAR, DEPi, DivI and DivA are presented graphically in the Descriptive Testing Appendix.
CAR	11.95%	18.84%	10.11%	20.43%		
DEPi	4.09%	3.63%	3.19%	2.43%		
DivI	0.66	0.73	0.79	0.71		
DivA	0.55	0.53	0.75	0.62		
Lg	11.00%	11.76%	18.80%	10.62%		
BR l-t average	1993-2008 avg		00.59	00.54		
Lg l-t-average			15.25%	8.93%		

Table 7:1:1. The table displays the results from the descriptive testing for each parameter. Tests have been conducted on the bank default periods of 1999-2002 and 2009-2010. The values are simple averages across all banks that belong to either the subgroup of failed banks in each respective period or

For the business risk parameter (BR), we observe that the subgroup of default banks consistently demonstrates higher values than the population total. It seems as if default banks on average maintain a higher standard deviation of their earnings/cash flows compared to the total, i.e. they display higher risk per dollar earned. This holds both for the short term and longer term (figs. A10-A15).

The outcome is expected. Higher standard deviation per unit of cash flows points to a lower risk-efficiency in the sense that the risk a bank takes to obtain its earnings is higher in proportion to the cash flows that risk yields. This being said, higher or lower risk-adjusted cash flows in reality may convey unclear information when it comes to the default probability of any one institution. A bank may have a "good"/low BR ratio but the underlying risk may be masked by very big cash flows. Riskier operations are expected to increase standard deviation, but the BR ratio could be left relatively unaffected as the cash flows are expected to increase as well, compensating for the increased risk. As such the BR measure, while being a potentially good measure of a bank's cash flow risk-efficiency, could be less good for actually assessing the underlying total risk of the bank.

For the capital adequacy ratio parameter (CAR), we discern a clear persistent pattern over time, where the subgroup of default banks on average has lower CAR values than the population of FDIC banks.

This is consistent with our expectations. Banks that subsequently fail have on average less capital adequacy i.e. they hold less dollars of capital per dollar of assets than do other banks and so may be less resilient against events that negatively impact e.g. their loan portfolios. The findings are in line with the fundamental reason for the CAR laid out by the BIS (capital adequacy matters for bank risk) as well as the findings of Acharya et al. (2011) (higher CAR -> lower risk of equity), Admati, et al. (2010) (better capitalization -> fewer distortions) and Das and Sy (2012) (high-RWA/higher asset risk banks perform worse) (figs. A16-A19).

On the other hand, banks that fail within a year cannot be expected to display adequate capital, as the shortage of capital is what usually leads to default in the first place. A one-year prediction period may be inadequate, as capital levels of failing banks may have been deteriorating some time. Even though our results point to the CAR as being a predictor at least one year prior to default – will it still be a good predictor over a longer horizon? Indeed this is the case. We model CARs for the total FDIC population and the subgroup of banks that default in 2009-2010 from 1992 to

2008 and observe that the average CAR values for failing banks are consistently lower compared to the total. Moreover the gap seems to widen at times of crisis. As such, the CAR seems to be able to distinguish banks that subsequently fail from others for as long back as 15-17 years before the event (fig. A4).

Looking at deposit interest rates (DEPi), we notice that default banks display higher interest rates (figs. A20-A23). Interest rates have declined between 1998 and 2008 but less so for the subgroup of default banks-to-be. Our findings corroborate those of Martinez-Peria and Schmukler (2001), Peresetsky et al. (2007) and to some extent Kraft and Galac (2007). The findings also hint about a behavior among banks discussed by Hellman et al. (2000) and Roland (2001), that some banks increase their deposit rates in order to attract capital used to finance risky assets.

This result merits regulatory concern. For a bank to be able to offer higher deposit interest rates, it will likely need to increase the return on its asset base. According to fundamental finance theory, an asset's expected return needs to increase with its underlying risk and vice versa (Berk and DeMarzo, 2007). A bank that offers higher deposit interest rates may be able to do so because its asset base is riskier than its peers. It yields higher rates of return and allows the bank to keep its profit margin unchanged as it increases its deposit interest rate to seek liquidity. Looking at the long-term, we map DEPi for the total as well as the subgroup of banks that fail in 2009-2010 over 1992-2010 and note that while the two groups track each other quite closely for most of the time, 2009-2010 failure banks start to deviate materially at around 2004 and thereafter display consistently higher average deposit interest rates than the total. At the onset of the financial crisis, interest rates are cut sharply but remain higher for defaulting banks throughout. Note that although both groups are very similar during the 1990s, default banks are mostly the ones that tend to have slightly higher interest rates (figs. A5-A6).

When it comes to income diversification (DivI), the pattern is inconsistent over time. For the period before 2003 default banks show a considerably higher degree of diversification compared to the total. In 2000, both groups reach are about equally diversified in terms of income and a general trend of diversification ensues for all. After 2003 however, this trend is broken and concentration picks up again. Not only does default bank concentration overtake that of the total but it also occurs at an increasing rate, creating a bigger and bigger gap between the two groups up to 2008 (figs. A2, A8). In 1998, default banks had a lower DivI average compared to the

total. In 2008, positions had switched. While the population at large had moved towards increased concentration up to 2008, default banks had done so much more aggressively (figs. A24-A27).

Over time the large portion of income from interest generating activities has been decreasing, from close to 70% in 1996 to just above 50% of total income in 2013. Up until 2003 this was the pattern of among banks. However, between 2003 and 2008, interest income rapidly increased from levels below 50% to above 60%.

The outcome of our tests seems to be in line with the findings of Altunbas et al. (2011) and could possibly point in the direction of what Elsas et al. (2010) find regarding bank profitability and valuation. Importantly, there are inconclusive connections to the research by e.g. Mercieca et al. (2007), Stiroh (2006), Stiroh and Rumble (2006) and Wagner (2010) who all suggest that increased diversification, especially into non-interest generating activities will heighten systemic risk and provide lower risk-adjusted returns. We evidently see that banks that later go into default on average carry more concentrated income streams than the total population. Note though that these studies are conducted on data for periods before the mid-00s, during which our results indeed are similar, as the subsample of default-to-be banks at that time actually displayed higher diversification. If they were measured to be relatively risky back then, we have an explanation for the sentiment that risker banks exhibit increased diversification.

We believe it is possible that the credit expansion that later proved to be one of the underlying causes of the financial crisis made banks move towards more concentrated income structures. If banks that were to fail during the crisis concentrated their income towards interest generating activities to a higher degree, possibly exposing those banks to a greater part of loans that later were to become "problematic", this could explain a great part of the development described above. Another major affecter of why income concentration did shift could be the level of the interest rate. Interest rate changes will directly impact the income composition as they affect the interest amounts generated by certain assets. If interest rates increase and the bank simultaneously grows its interest-generating activities, a double-effect is obtained that will lead to even faster concentration of income.

Turning to asset/loan portfolio diversification (DivA), we observe persistence over time. Default banks are consistently more concentrated on average

than the FDIC bank population. Compared to income diversification, the relationship between failure and asset concentration seems more clear-cut (figs. A28-A31).

If we look at banks' loan composition over time, it is noticeable that share of real estate-secured assets, while remaining fairly level over the 90s, increased between 2000 and 2006, to later decline back to the 90s' levels and below. What is also interesting is that at the same time real estate started to increase, commercial and industrial loans declined, while most other loan classes remained relatively unchanged (figs. A3, A9).

We once again connect back to the literature on the topic as discussed in the section for DivI above. While some of our results are consistent with previous research, others are not. We clearly see the use of older data in other studies as key to the discrepancies. The long-term effect of diversification is measured in our study by having banks that defaulted in 2009-2010 as our failure subgroup measured from 1992. However, other studies do not use data that cover the period of the latest financial crisis, these banks were still "alive and kicking" in, say 2003 and most certainly throughout the nineties. As such we cannot get away from thinking that the time period of measurement and the different causes and natures of crises play a very big role when it comes to evaluating the riskiness of banks' characteristics.

Our findings for DivA connect to the discussion on income diversification. It is imaginable that banks started to pursue the residential real estate market more aggressively after the turn of the millennium, compensating this effort by reducing commercial loans. As the crisis built up, banks' loan portfolios became increasingly concentrated, also showing on their income, which too became more concentrated. Post-crisis loan composition has basically reverted to what is observed during the 1990s and so has income composition.

Lastly, we turn to loan portfolio growth rates. For the long-term period of 1993-2008 banks that were to fail in 2009-2010 exhibited much higher Lg on average (figs. A36-A37). Looking at the sub period of 1993-1998 Lg for 1999-2002 fails the relationship was the opposite. The other sub period of 2003-2008 shows that fail banks tended to grow faster. Overall, it seems as if loan growth affects the likelihood of a bank default, both for shorter and longer horizons (figs. A32-A35). With little room for argument, the findings are consistent with those of e.g. Köhler (2012) and logically also Foos et al. (2010).

The Lg results connect to the discussions on income and asset diversification. As default banks have shown a higher average loan growth in general, this could be founded on rapid credit expansion into riskier assets from the early 2000s to about 2007, as demonstrated by the graphs on income and loan composition development. The fact that the sub period of 1993-1998 points to basically the same average growth rates for defaults and total population strengthens the proposition that this expansion started some time after this period and that default banks took a more aggressive stance once the expansion commenced.

Please refer to the Descriptive Testing Appendix for graphs.

7.2 Inferential Testing

Univariable regression testing

We first run univariable logistic regressions for each variable observed in 1998 and 2008 on the two periods 1999-2002 and 2009-2010 of bank failures.

Summary Table of Inferential Testing				
	Univariable Odds Ratios		BR and Lg are estimated as five-year *annual* averages for 1993-1998 and 2003-2008 respectively. Other parameters are single observations at 1998 and 2008 respectively.	***indicates significance at the 1% level, **indicates significance at the 5% level, *indicates significance at the 10% level
	Test Period			
Parameter	1998 on 1999-2002	2008 on 2009-2010		
BR	54.38***	56.19***		
CAR	4.69e^-17***	1.30e^-33***		
DEPi	4.28e^7	2.70e^63***		
DivI	0.02***	24.86***		
DivA	1.00	100.08***		
Lg	0.96	13.14***		

Table 7:2:1. The table displays the results from the univariable inferential testing for each parameter. Tests have been conducted on the bank default periods of 1999-2002 and 2009-2010. The values are simple averages across all banks that belong to either the subgroup of failed banks in each respective period or the total FDIC number of banks.

For BR, we observe a consistently strong positive relationship with bank failures, i.e. as the value of BR increases, so does the likelihood of default. Comparing this to the corresponding findings in the descriptive section, we conclude that the pattern persists. Banks with higher BR display a worse risk-return trade off. Our view is also reiterated: while BR as specified here may be a potentially good measure of a bank's cash flow risk-efficiency, it could be less good for actually assessing the underlying comprehensive risk of the bank, which is what should matter for deposit insurance.

For CAR, our findings are consistent with our beliefs that the CAR is a good predictor of bank default risk and that a decrease in capital adequacy will increase

the probability of default. This also conforms to our findings in the descriptive section. The CAR seems to be a good explanatory variable for bank defaults.

For DEPi, the statistics indicate a positive relationship between deposit interest rates and bank default risk; but the 1998 result is not statistically significant (P>z = 0.228). Our overall impression remains: A bank that on average offers higher interest rates on deposits is more likely do subsequently go into bankruptcy. This relationship is expected and also corresponds to our findings in the descriptive section.

For DivI the odds ratio in 1998 points toward a decreasing relationship, i.e. a higher concentration lowers the probability of default, while the 2008 result indicates that higher concentration in income sources constitutes an increased risk of default for banks. These results are just what we expect, considering the fact that defaulting banks were more income-diversified prior to 2003 and got more concentrated income structures thereafter. Income concentration towards interest-generating activities will have the effect that interest rate declines or an increasing rate of loan delinquencies have greater impact on the banks' revenue generating capabilities. While concentration may have been a strong indicator of problem banks during the financial crisis, the millennium crisis was of another nature and it could be that factors other than DivI played a bigger role in 1998 compared to 2008.

For DivA, the 1998 test indicates no effect on bank default risk (estimate is not significant, P>z = 0.992) while there is a strong positive relationship in the 2008 test. Just as mentioned about DivI, an increased loan portfolio concentration is linked to a higher likelihood of default in the later crisis but seems to not matter for the millennium crisis. As discussed earlier, it is conceivable that banks started to pursue the residential real estate market more aggressively a few years into the new millennium, compensating this effort by reducing commercial loans. As the financial crisis built up, loan portfolios of such banks became increasingly concentrated, also noticeable on income, which too became more concentrated. As these assets became distressed in 2007-2008, banks that had put a lot of weight into them became increasingly strained and a higher degree of those banks did fail compared to the total. Even though failure banks seem to have always had a greater loan concentration, as mentioned under DivI, their aggressive behavior seems to have started after the millennium. The 1999-2002 default period was most likely not affected and therefore concentration variables looks to be less good indicators in

1998 than in 2008. We are again reminded that crises are founded on and fueled by different factors.

Turning finally to Lg, the 1998 estimate is not significant (P>z = 0.978). The 2008 estimate is indicative of a positive relationship between the average five-year growth rate of the loan portfolio and default risk. This corresponds well to what we stated in the descriptive section and is expected. As we mentioned, failure banks showed a higher average loan growth in general over the period 2003-2008 and it is not improbable to suggest that this was founded on rapid credit expansion into a specific, possibly riskier asset class from the early 2000s until the outbreak of the financial crisis. The 1998 estimate points to the reverse, with a negative (but insignificant) relationship. Connecting once again to the discussion in DivI and DivA, as the two crises differ considerably in size and nature, it is not improbable that some of the estimates differ in magnitude, sign and significance over time.

On a finishing note, we must highlight that the 1999-2002 failure period comprises only 30 banks compared to the 304 banks that failed between 2009-2010. This will of course have implications for the statistics when the regression models are run on 1998 data. We must take this into consideration when we assess the number, magnitude, sign and significance of the estimates. While for instance the CAR holds magnitude, sign and significance in both the 1998 and 2008 data, the same is not true for Lg. As the data is much more comprehensive for the 2008 period, it is perhaps easy to place more weight on this period. On the other hand, like most unexpected events, the financial crisis had its own characteristics and causes, making it different from past and most likely future crises. The ideal would be to find parameters that retain approximately the same features over time and crises, as these could arguably provide a fee model with more robust fee determination. In our case, BR and CAR seem to bear at least some of such resemblance.

Multivariable regression testing

We next turn to multivariable logistic regression testing. We test all our parameters on 1999-2002 and 2009-2010 failure periods.

Summary Table of Inferential Testing			BR and Lg are estimated as five-year *annual* averages for 1993-1998 and 2003-2008 respectively. Other parameters are single observations at 1998 and 2008 respectively.	***indicates significance at the 1% level, **indicates significance at the 5% level, *indicates significance at the 10% level
	Multivariable Odds Ratios			
	Test Period			
Parameter	**1998 on 1999-2002**	**2008 on 2009-2010**		
BR	48.98***	8.47***		
CAR	3.72e^-15***	8.53e^-28***		
DEPi	2.77e^13	6.39e^54***		
DivI	0.26	0.31		
DivA	0.67	41.10***		
Lg	0.10	0.46		

Table 7:2:2. The table displays the results from the multivariable inferential testing for each parameter. Tests have been conducted on the bank default periods of 1999-2002 and 2009-2010. The values are simple averages across all banks that belong to either the subgroup of failed banks in each respective period or the total FDIC number of banks.

The 1998 multiple variable model specification provides only two significant parameters: BR and CAR. As evident from the single regressions, the 1998 test is generally weaker compared to the 2008 test, as there are fewer defaults to include. But not to forget, the 1999-2002 crisis was of a different nature and occurred for different reasons than the financial crisis. As such, variables that explain defaults during the financial crisis may not explain defaults equally well in other crises. Nevertheless, that both BR and CAR remain significant in a multiple setting indicates their potency as default predictors, as was the case in the univariable setting.

The 2008 data model specification implies that DivI and Lg lose significance in predicting bank default risk. All other parameters remain significant down to the 1% level.

In terms of interpreting the model, we note that Prob > chi2 is 0.0000 in both cases, which generally indicates that the models as a whole are significant. A pseudo R2 of 0.17 for the 1998 model and 0.37 for the 2008 model is expected considering the relatively small amount of variables included compared to possibly hundreds of variables that may affect bank default risk. The lower R2 value for the 1998 data probably derives from fewer significant parameters and possibly testing the "wrong" parameters for that crisis.

Testing reduced models

Summary Table of Inferential Testing			BR and Lg are estimated as five-year *annual* averages for 1993-1998 and 2003-2008 respectively. Other parameters are single observations at 1998 and 2008 respectively.	***indicates significance at the 1% level, **indicates significance at the 5% level, *indicates significance at the 10% level
	Multivariable Reduced Odds Ratios			
	Test Period			
Parameter	**1998 on 1999-2002**	**2008 on 2009-2010**		
BR	22.09***	6.35**		
CAR	8.25e^-15***	3.04e^-27***		
DEPi	-	2.01e^49***		
DivI	-	-		
DivA	-	35.46***		
Lg	-	-		

Table 7:2:3. The table displays the results from the multivariable reduced inferential testing for each parameter. Tests have been conducted on the bank default periods of 1999-2002 and 2009-2010. The values are simple averages across all banks that belong to either the subgroup of failed banks in each respective period or the total FDIC number of banks.

Running the regressions again after removing insignificant variables yields no material changes with respect to significance or explanatory power. Relationships, signs and significances remain unchanged at the parameter level and signs are all in the expected directions.

Please refer to the Inferential Testing Appendix for additional tables and details regarding collinearity, correlation, specification, goodness-of-fit, influential cases and linear assumption tests.

7.3 The Current Swedish Fee Model Applied on the U.S. Banking System

We apply the Swedish fee model on the U.S. banking system and note that fee payments flow into the fund once per year (the real U.S. fee is actually paid once per quarter) and costs are modeled as they occur. Looking at annual payments versus annualized costs (i.e. costs summed up over the course of a year), the only years that run a deficit on their own are 2009, 2010 and 2011. All other years manage to carry their annual DIF costs solely on their fee income. This is an important observation as it tells us that the fund in most cases can survive from year to year without having to rely on built-up means from previous years (fig. A38).

Looking at annual fee payments versus running costs (i.e. costs are mapped as they happen rather than annualized), the fund displays a stepwise increasing pattern as funds enter the system, accumulate and subsequently decrease as losses occur. The interesting part is the financial crisis period. From the end of 1992 up until the end of 2008, the DIF accumulates approximately USD 65 billion. As the crisis hits however, this balance is greatly reduced and in less than a year it has

turned into a deficit. The deficit persists through 2012 and the fund shows zero balance at the start of 2013 (figs. A39-A40).

This pattern is expected in a deposit insurance system. Remember that we look at the fund system in general and so far are not concerned with the risk differentiation among individual banks. The DIF shows good resilience against single, sporadic or so-called idiosyncratic shocks but cannot seem to resist the pressure of a big systemic crisis. As with any other insurance system, clients (banks) pay premiums to insure themselves against damage (defaults/bank runs). As long as only an expected amount of clients experience trouble over any time period, the insurance company (the FDIC) can cover the losses via its reserves (the DIF) and reimburse the clients. However, as a systemic crisis hits, basically all or many more clients will experience problems at once, making the total expenditures surmount the capability of the insurer and the reserves are fully depleted. The chain of development during the financial crisis lead to extremely high costs for the DIF and it was depleted. This is not strange, it only points to the difficulty to prepare for the unexpected - the "tail loss".

This exercise serves to assess how well the Swedish fee model would have worked in the U.S and our conclusion is that it appears to work as expected. A thing we would have found beneficial is to compare the Swedish and the U.S. fee systems. This has not been possible as the U.S. DIF fee is included in a single item of various other expenses in the bank data and is not separable. Also, compared to the Swedish fee, the U.S. fee is determined in part from scorecards using the CAMELS[39] rating system, which includes bank specific, non-public information. It is therefore hard to even estimate a U.S. fee. Please refer to the Empirical Fee Model Testing Appendix.

Even though the fund as a whole seems to perform well as far as default coverage goes, it does not say anything of the fairness in setting the fees to banks of different risk characteristics. This is something we look into next.

7.4 The Simulation Model Run Using the Fee Models

We test our various simulation models for the Swedish fee model (SWE, ELP and UPD) on the U.S. system under the scheme in section Model/Simulation Method. The

[39] The CAMELS rating system is a system developed in the U.S. to classify a bank's overall condition. It comprises the components (C)apital adequacy, (A)ssets, (M)anagement capacity, (E)arnings, (L)iquidity and (S)ensitivity to risk.

results are presented below. Refer to the Simulation Model Appendix for graphical presentations and model details.

The appendix graphs show the DIF net positions[40] split by model, scenario and bracket (red line is the cumulative net across brackets) (figsA41-A43). As described earlier, in the Swedish model each bank is assigned a bracket 1-9 classification depending on its relative CAR, where a bank with the highest CAR relative to the other banks ends up in bracket 1, the bank with the next highest CAR in bracket 2 and so on. We display DIF nets (fees paid less default costs incurred) on a per-bracket basis since it is easier to judge where banks tend to pay less, adequately or more than needed to cover the default costs they cause. One can say this way of showing the DIF results corresponds to a hypothetical multi-fund system, in which each cluster of bracket 1-9 banks pays and extracts funds from separate DIFs depending on to which brackets they are assigned. A positive bracket net position indicates that banks belonging to that bracket collectively have paid more than the costs they have caused to the DIF and vice versa. DIF net positions differ quite a lot between brackets and scenarios, both within and between models. No model manages to maintain relatively unchanged balances across the testing scheme.

Scenario	**Total net**		
	100% SWE	ELP	UPD
1yr avg PD	**-1 270 792**	**-1 206 521**	**-320 410**
1yr min PD	**1 800 000**	**0**	**2 330 900**
1yr max PD	**-22 369 908**	**-13 340 829**	**-21 814 147**
5yr avg PD	**-10 735 372**	**-4 886 590**	**82 977**
5yr min PD	**489 085**	**-755 377**	**12 128 405**
5yr max PD	**-140 858 418**	**-112 806 311**	**-130 926 299**

Table 7:4:1. The table displays the outcome of the simulation model testing for the three models SWE (real Swedish model), ELP (Swedish model with expected loss pricing) and UPD (Swedish model with additional parameters). Scenarios are run as specified in section 6.3.

The table above displays the total DIF net for each scenario and model, i.e. the sum of all nine bracket columns for a run. This is consistent with the current single DIF to which fees are paid and from which costs are distributed. Over the full

[40] *The net position amounts are summed over 10,000 simulation runs, so this must be put in proportion to the steady deposit level of USD 20,000 per bank, which holds for each one of the single runs. If a bank ends up paying USD 30,000 too much over 10,000 runs, this is analogous to it paying 3 too much per run, or 3/20,000 = 0.015% too much in relation to its level of deposits etc.

test range, it looks as if ELP displays the lowest dispersion. Looking at only the one-year horizon tests, we see that UPD provides the best result on the average scenario and ELP on the minimum and maximum scenarios. ELP performs better than SWE across all one-year scenarios while UPD performs worse for the minimum case. For the five-year horizon tests, we observe that SWE performs best in the minimum case, ELP performs best in the maximum case and UPD performs best in the average case. Evidently, each model performs either better and worse than the others based on what scenario is at hand. This opens up for ambiguity, as we can never be sure beforehand what real-world scenario will occur and the fees are set ex-ante. Remember that (simplified) we do not want the DIF to run either a surplus or deficit but a zero net position since the money should only cover deposits at default banks. Forecasting over a five-year horizon entails greater uncertainty both in model specification and possible real world outcomes and we are extra careful to judge the five-year results (fig. A44).

Not entirely unexpected, the one-year best-case scenarios produce zero positions for ELP. Under ELP banks do not pay anything since there are no defaults expected (all PDs are 0%). Any scenario where ELP runs either a surplus or deficit indicates that defaults were either less or more than expected. If the frequencies of expected and actual defaults matched, ELP would always produce zero net positions.

While results are inconclusive as to what actually makes a model less dispersive than another, they nonetheless speak against risk differentiation via the CAR alone. Net positions vary a lot between brackets in SWE; with banks almost always paying too little or too much (see again the bracket-by-bracket graphs). We can at the same time conclude that by simply modifying the model to estimate fees according to ELP instead, overall fund performance improves visibly albeit not perfectly.

7.5 Backtracking Default Banks

More than 60% of banks that fail are in bracket 9 at the time of failure. But the question is if bracket 9 banks should carry a higher proportion of costs over time. If a certain group of banks voluntarily causes these high risks by continually having low CARs, then this might be reasonable. But if, however, banks often fall to lower CAR categories just before defaulting, then by imposing higher costs for low relative CARs, we are in fact punishing banks that are temporarily in distress. As we expect

some mobility between brackets, the extreme 60% case is probably not true. Furthermore, we do not expect all costs of banks to be covered by last year contributions. Therefore, we studied the relative CAR movements of banks in the years leading up to failure.

Banks' brackets are tracked backwards – and as predicted, we observe that the closer to default a bank is the lower the likely bracket. The last couple of years show the strongest deterioration. When we look at average bracket score for a year, where -1 represents one year before default, then -1 gives almost 8 average, with scores reaching average when we get down to -20. This indicates that in the long run, banks that fail might have been quite average.

Year	**-20**	**-19**	**-18**	**-17**	**-16**	**-15**	**-14**	**-13**	**-12**	**-11**
n	8	39	79	170	258	282	291	303	323	349
Δ bracket		0.647436	0.039273	0.41035	0.242088	-0.03241	0.188967	0.09918	-0.07089	0.019702
μ bracket	4.25	4.897436	4.936709	5.347059	5.589147	5.556738	5.745704	5.844884	5.773994	5.793696
Year	**-10**	**-9**	**-8**	**-7**	**-6**	**-5**	**-4**	**-3**	**-2**	**-1**
n	379	406	425	450	479	497	522	543	551	552
Δ bracket	0.013692	0.140888	0.105842	0.074771	0.03395	0.09873	0.221189	0.266781	0.40654	0.813123
μ bracket	5.807388	5.948276	6.054118	6.128889	6.162839	6.261569	6.482759	6.74954	7.15608	7.969203

Table 7:5:1. The table displays the outcome of the backtracking testing for banks that subsequently default. *Year* indicates the number of years before actual default that banks are observed, *n* is the number of banks observed at each observation point, *Δ bracket* is the incremental change in aggregate bracket value for the group of banks observed and *μ bracket* is the mean aggregate bracket observed.

Based on these bracket scores, we calculate a standardized and a non-standardized cost and fee payment time for all banks. In the standardized measure, we assume all banks are of equal size and calculate (1) the amount of time each bank spend paying in any bracket before default, and (2) the product of percentage loss given default divided by brackets. We then do the same for non-standardized data, (3) the fees depending on deposits guaranteed and the (4) costs on realized losses in dollars. Please see further in Backtracking Appendix.

Our backtracking definitely shows that the time horizon matters and it most clearly tells about the range of the fee today. The way the Swedish fee is constructed, it allows for a maximum difference of 2.33 between the lowest and highest fees. In the 3-year horizon, differences in costs between brackets 1 and 8-9 are a factor of more than 90 in both cases. The 2.33 factor would be tantamount to a very long-term perspective of bank payment time. If we assume that no interest is accrued and that banks' distributions among brackets are random more than 15 years back, our simulations (based on 500 iterations of a distribution where brackets are random from 16 years back) show that it represents about a 43-year perspective. While

adding an interest factor is surely reasonable to account for the time value of money, it is certainly difficult to assess what reasonable returns are. The result is that the current fee system is fair – over certain time horizons. These are roughly between 45 years and 30 years, depending on interest rate assumptions.

8 Summary and Conclusions

This section summarizes the main findings and their implications for the development of a new deposit insurance fee model as well as some issues to consider. The research questions are revisited and some answers are provided in the light of the research carried out.

8.1 On Future Model Choice for Riksgälden

The current fee system seems to provide a sufficient amount of money, given that large crises are rare. While the model is quite simple on its own – it places all emphasis on the CAR, which relies on very complex RWA calculations.

8.1.1 Simplicity

Some authors worry that using the CAR as basis might lead banks to choose suboptimal capital structures – equity being expensive. This is quite strongly refuted by others, including Admati et al. (2010). Either way, by employing more factors, the risk that banks behave too extremely in terms of capital structure is mitigated. Another concern is that RWA rules can be "optimized", as banks focus mostly on compliance, as Evanoff and Wall (2000) point out. RWA has fallen since banks were allowed to determine it themselves. Confidence in RWA has fallen, and academic focus on it is limited. Using more measures makes optimizing CAR less important. This speaks for using more measures. Simple models do have advantages, as Haldane (2012) and others point out. However, we do not consider simplicity a strong argument for keeping the current model.

8.1.2 Fairness

We treat fairness mostly as fairness between banks. The deposit insurance must not carry all costs to the state, since other funds, like the stability fund, help. But banks should get the right incentives and the fee structure should not unduly disadvantage some banks. The intra-bank fairness looks different depending on which time horizon we look at. Low fee differentiation is fair if costs are calculated long term.

We find the Swedish fees to work thus. Larger differentiation could be used to create greater incentives in the short run. We might hold costs that take 30 or more years to be reflected have too little effect on behavior now. Decisions dictate the extent to which banks shift risks to taxpayers. Fairness and moral hazard are thus connected. We have seen suggested that many historic fee systems created moral hazard, and must therefore think of short term incentives too. We believe that while the current system reflects very long term fairness, we might want to take a more short term view, so that banks experience fairness during their planning horizon. Therefore, we see advantages in higher fee differentiation.

8.2 Considerations

Since the Swedish banks' contribution to the deposit insurance fund is determined by their relative risk weighted capitalization, one way of amending the system is to keep the current deposit insurance rules, but change the risk weight rules, something that recently has happened in the case of mortgages (floor of 15%, May 2013) and currently is about to happen, again primarily regarding mortgages (floor of 25%, spring 2014). Also, it is not clear that the latest Basel rules need to be used for calculating CAR. Basel I rules might be of a more adequate complexity for the model, cannot as easily be "optimized", and do not change with time. Another approach would be using a multivariate model.

8.2.1 Suggestion – A Simple Multivariate Model

Very sophisticated models are not our strongest recommendation, as advantages seem dubious. We prefer a simple multivariate model. Below, discuss the parameters we investigated. Our tests have shown that some of our parameters have potency as predictors and proxies of bank default likelihood..

Business risk, as measured, shows promise. High variation in profits is not something we mind discouraging – we do not see this discouragement creating any new moral hazard[41]. We would encourage using a business risk measure for multivariate models.

Banks that default show higher **deposit rates** and the underlying logic in the argument for this variable makes sense: banks that pay higher deposit rates need to achieve higher returns, implying more risk. Deposit rates can, as we saw, serve as an

[41] Firms already strive to smooth income for a lot of reasons, such as tax, covenants and to enhance firm value and it is debatable whether effects are negative: Tudor, Alexandra (2010)

early warning signal. Also, using deposit rates might reduce moral hazard and serve as a counterweight to the effect Hellman et al. (2000) describe: if regulation focuses on capital adequacy and ignores deposit rates, then banks might have an incentive to increase deposit interest rates to gain funding for increasing asset risks. Thus, the measure improves CAR. Problems include that the measure is politically sensitive since it punishes banks that give more to customers and it can be seen as interfering in banks' competition by interest. Such competition can be seen as a form of moral hazard that shifts risk to the fund. We are positive to the measure, if it is not given too much weight.

While using **diversification** measures is attractive since they can reflect the level of idiosyncratic risk, this is one of the more complicated ones to construct. In our tests the asset diversification variable has worked more consistently than the income based one. Diversification measures might lead banks to assume unsuitable strategies to increase diversification for its own sake, even when researchers are divided in terms of what benefits come out of increased diversification and what risks it entails. We are not positive to using diversification.

Loan growth is an interesting variable, but can definitely present an entry barrier. It should be considered to look at ways of mitigating the effect on new entrants, such looking at loan growth in some combination of absolute and relative terms. We see loan growth as a possible candidate for use,

On a finishing note, the CAR, often having seen its perceived credibility as a risk measure fluctuate, earns strong support in our study. We see it as the strongest standalone factor – a fee system based on only for instance deposit rates would be hard to argue for. We believe CAR certainly has a future as a risk indicator, a fee agent and as a part of an early warning system of bank default risk. It should not be abandoned but rather, it seems to have historically been assigned more heavy duties than it should. As part of a multivariate system, we see potency in the CAR; while being aided by a support system of carefully selected parameters, to contribute in setting future deposit insurance fees more fairly and adequately than before.

8.3 Connecting Back to the Research Questions

1. Our work shows that the potency of the CAR alone as a risk-differentiator is limited in the sense that banks tend to either over- or underpay for deposit insurance ex-ante compared to the ex-post costs they impose on the DIF. It is neither

simple nor fair short term. However, we find that the CAR appears to be a strong predictor of bank default risk. Both our descriptive and inferential analyses point to the CAR as being a measure that is applicable when one wants to detect banks that have a relatively higher likelihood of failure. This holds also in the multivariable setting. Our tests are constant enough to make us believe that is in fact the case.

We are also of the opinion that it is not implausible to think that the fee model specification as such contributes to mispricing. Fairness can be altered somewhat by simply changing the way CAR is used – i.e. increasing the spread. We must realize that it is a lot to ask from a single variable to perfectly or even satisfactory differentiate among institutions in such a complex environment.

It is our belief that an updated version of the fee model can be beneficial for increasing the fairness and adequacy of fees paid. Results from the implementations of the ELP and UPD models point to this. Furthermore, the improvement in fee setting by employing the quite straightforward ELP version indicates that a change of model does not necessarily have to entail a long, costly and complex process.

2. Testing the parameters of interest reveals that some seem to perform better than others in terms of consistency over time (BR, CAR). While all parameters prove significant in the later testing period, most do not in the earlier one. Whether this is due to the parameters per se or to the different cause and nature of crises are up for debate, but we lean towards the latter. Including more variables in a model does not guarantee its viability and may also result in greater cost for building and maintenance. It can also increase the risk of misspecification.

We believe that while the model certainly can benefit by adding a few more parameters besides the CAR, adding a lot of variables will rather cause adversities. Riksgälden needs to carefully consider what additional parameters to include. Our study has hopefully pointed out a few good candidates.

3. Our backtracking procedure provides an indication of what time frames are at play for spotting potential future trouble-banks. Likewise do the long-term parameter analyses, which show that subsequently defaulting banks consistently score differently than others on measures such as BR, CAR and DivA. These findings can help improve forecasting in the setting of fees and fund levels and provide regulators with increased time-action potential both in mitigating and preventing defaults. While our work has provided some answers on the workings of bank

default risk, different models and potential parameters, several questions demand answers from future research. We believe that the development process of new and better deposit insurance fee models can greatly benefit from testing more variables, using more model specifications, over longer time periods, incorporating more crises and on more deposit insurance systems. Here, studies by Laeven (2002) and Demirgüç-Kunt and Kane (2002) and Demirgüç-Kunt (1989) provide useful ideas.

9 Discussion

This section provides a brief concluding discussion about a few interesting insights.

9.2 What About the Fee Model for the Stability Fund?

Another important and new part of the financial safety net in Sweden is the stability fund which is a fund dedicated to the support of distressed banks before their de-facto default. Riksgälden has during our discussions raised the question of a future modification with respect to risk differentiation of the stability fund fee as well.

However, we think that a risk-adjustment for the stability fund must be done on a different basis compared to that of the deposit insurance fund. This is due to the fundamentally different purposes of the two funds. The stability fund aims to aid distressed banks through assistance transactions, commonly via equity investments. It is improper to label these transactions simply as expenditures. As has been shown both in the U.S. and Sweden after the latest financial crisis, the majority of assistance transactions have yielded positive returns for the governments. For example the Swedish government investments in Nordea in 2009 have yielded a 44% per year return.[42]

The connection between the stability fund and the deposit insurance fund remains strong. The more banks saved before bankruptcy, the lower the costs for Riksgälden's deposit insurance. The relationship is however not linear, and represents an interesting area of further research.

[42] Riksgälden (Ref # 2)

10 Method Evaluation

The final section presents an evaluation and thoughts about the methods used.

Our basic approach of looking at how the current fee system works in a realistic setting has many advantages: mainly the broad and detailed database. Complications arise from differences between Sweden and the U.S., discussed in detail above. We believe our STATA regressions, combined with academic research, help show which of Riksgäldens`s suggested variables have more potential. Simulating different fee models has limitations, as there are endless possible variations and we cannot test them all. Nevertheless they give an indication that the current fee model is doing a decent job in terms of relative variance. Using CAR brackets might be novel, but it found many useful applications. Of course, it is not in terms of CAR brackets, but actual real default probabilities that banks should be sorted. But that will always only be a theoretical ideal. Brackets are good tools to increase understanding and see if there is balance and fairness. Our backtracking model sheds an important light on the time horizon of the model, also using the brackets and other categories, like the current American fee groups, prove less useful. The inclusion of a descriptive and an inferential part to the method makes it more rigorous and complete. We have striven to do many different tests to get many different aspects – but the limited time and space of the thesis work definitely represent constraints that made the use of so complex and inclusive methods harder. Naturally, the robustness of our findings could have benefitted from using some more descriptive characteristics and a wider set of regression model specifications. We believe that our procedure at least point in relevant directions and it will be up to the regulator to proceed with added research to investigate the relationships further. There is also the obvious issue of using U.S. data for a Swedish model. This is however discussed in detail in the data section above and we continue to stress both the similarities and differences one must consider when evaluating the results and the implications coming from this paper.

References

Periodicals

Admati, Anat Anat R. Admati, Peter M. DeMarzo, Martin F. Hellwig and Paul Pfleiderer, 2010, Fallacies, Irrelevant Facts, and Myths in the Discussion of Capital Regulation: Why Bank Equity is Not Expensive. No. 2010, 42. Preprints of the Max Planck Institute for Research on Collective Goods.

Baele, Lieven, Olivier De Jonghe and Rudi Vander Vennet, 2007, Does the Stock Market Value Bank Diversification?, Journal of Banking & Finance 31.7, 1999-2023.

Barth, James R., Gerard Caprio Jr and Ross Levine, 2004, Bank Regulation and Supervision: What Works Best?, Journal of Financial Intermediation 13.2, 205-248.

Berger, Philip G., and Eli Ofek, 1995, Diversification's Effect on Firm Value, Journal of Financial Economics 37.1, 39-65.

Blundell-Wignall, Adrian, and Paul Atkinson, 2010, Thinking Beyond Basel III: Necessary Solutions for Capital and Liquidity, OECD Journal: Financial Market Trends 2010.1

Bongini, Paola, Luc Laeven, and Giovanni Majnoni, 2002, How Good is the Market at Assessing Bank Fragility? A Horse Race Between Different Indicators, Journal of Banking & Finance 26.5, 1011-1028.

Borensztein, Eduardo, Kevin Cowan, and Patricio Valenzuela, 2013, Sovereign Ceilings Lite? The Impact of Sovereign Ratings on Corporate Ratings, Journal of Banking & Finance 37.11, 4014-4024.

Calomiris, Charles W, 1990, Is Deposit Insurance Necessary? A Historical Perspective, The Journal of Economic History 50.02, 283-295.

Castanias, Richard, 1983, "Bankruptcy Risk and Optimal Capital Structure, The Journal of Finance 38.5, 1617-1635.

Chen, Yehning, 1999, Banking Panics: The Role of the First-Come, First-Served Rule and Information Externalities, Journal of Political Economy 107.5, 946-968.

Cooperstein, Richard L., George G. Pennacchi and F. Stevens Redburn, 1995, The Aggregate Cost of Deposit Insurance: A Multiperiod Analysis, Journal of Financial Intermediation 4.3, 242-271.

Demirgüç-Kunt, Asli, 1989, Deposit-Institution Failures: A Review of Empirical Literature, Economic Review 25 No. 4, 2-19.

Demirgüç-Kunt, Asli, and Harry Huizinga, 1999, Determinants of Commercial Bank Interest Margins and Profitability: Some International Evidence, The World Bank Economic Review 13.2, 379-408.

Demirgüç-Kunt, Asli, and Edward J. Kane., 2002, Deposit insurance around the globe: where does it work?, The Journal of Economic Perspectives 16.2, 175-195.

Demirgüç-Kunt, Asli, Edward J. Kane, and Luc Laeven, 2008, Determinants of Deposit-Insurance Adoption and Design, Journal of Financial Intermediation 17.3, 407-438

Diamond, Douglas. W. and Philip H. Dybvig, 1983, Bank Runs, Deposit Insurance and Liquidity, Journal of Political Economy 91, No. 3, 401-419.

Duffee, Gregory R., 1999, Estimating the Price of Default Risk, Review of Financial Studies 12.1, 197-226.

Elsas, Ralf, Andreas Hackethal, and Markus Holzhäuser, 2010, The Anatomy of Bank Diversification, Journal of Banking & Finance 34.6, 1274-1287.

Englund, Peter, 1999, The Swedish Banking Crisis: Roots and Consequences, Oxford Review of Economic Policy 15.3, 80-97.

Ennis, Huberto, and Todd Keister, 2010, On the Fundamental Reasons for Bank Fragility, FRB Richmond Economic Quarterly 96.1, 33-58.

Estrella, Arturo, Sangkyun Park, and Stavros Peristiani, 2002, Capital Ratios and Credit Ratings as Predictors of Bank Failures, Federal Reserve Bank of New York: Economic Policy Review, 33-52.

Ferri, Giovanni, L-G. Liu, and Joseph E. Stiglitz, 1999, The Procyclical Role of Rating Agencies: Evidence from the East Asian Crisis, Economic Notes 28.3, 335-355.

Foos, Daniel, Lars Norden and Martin Weber, 2010, Loan Growth and Riskiness of Banks, Journal of Banking & Finance 34.12, 2929-2940.

Fries, Steven, Robin Mason, and William Perraudin, 1993, Evaluating Deposit Insurance for Japanese Banks, Journal of the Japanese and International Economy 7, 356-386.

Hellmann, Thomas F., Kevin C. Murdock, and Joseph E. Stiglitz, 2000, Liberalization, Moral Hazard in Banking, and Prudential Regulation: Are Capital Requirements Enough?, American Economic Review, 147-165.

Hovakimian, Armen and Edward J. Kane, 2000, Effectiveness of Capital Regulation at U.S. Commercial Banks, 1985 to 1994, Journal of Finance 55, 451-468.

Hovakimian, Armen, Edward J. Kane, and Luc Laeven, 2003, How Country and Safety-net Characteristics Affect Bank Risk-Shifting, Journal of Financial Services Research 23.3, 177-204.

Jones, David S., and Kathleen Kuester King, 1995, The Implementation of Prompt Corrective Action: An assessment, Journal of Banking & Finance 19.3, 491-510.

Kale, Jayant, Thomas Noe and Gabriel Ramirez, 1991, The Effect of Business Risk on Corporate Capital Structure: Theory and Evidence, The Journal of Finance, 46, No. 5 1693-1715.

Keeley, Michael C, 1990, Deposit Insurance, Risk, and Market Power in Banking, The American Economic Review, 1183-1200.

Kraft, Evan, and Tomislav Galac, 2007, Deposit Interest Rates, Asset Risk and Bank Failure in Croatia, Journal of Financial Stability 2.4, 312-336.

Kwan, Simon H., and Elizabeth S. Laderman, 1999, On the Portfolio Effects of Financial Convergence: A Review of the Literature, Economic Review 2, 18-31.

Laeven, Luc, 2002a, Bank Risk and Deposit Insurance, World Bank Economic Review, 16(1): 109-137.

Lepetit, Laetitia, Emmanuelle Nys, Philippe Rous and Amine Tarazi, 2008, Bank Income Structure and Risk: An Empirical Analysis of European Banks, Journal of Banking & Finance 32.8, 1452-1467.

Longstaff, Francis and Eduardo S. Schwartz, 1995, A Simple Approach to Valuing Risky, Fixed and Floating Rate Debt, The Journal of Finance 50.3, 789-819.

Madan, Dilip and Haluk Unal, 1998, Pricing the Risks of Default, Review of Derivatives Research 2.2-3, 121-160.

Merton, Robert C., 1974, On the Pricing of Corporate Debt: The Risk Structure of Interest Rates, The Journal of Finance 29.2, 449-470.

Merton, Robert C., 1977, An Analytic Derivation of the Cost of Deposit Insurance and Loan Guarantees an Application of Modern Option Pricing Theory, Journal of Banking & Finance 1.1, 3-11.

Peek, Joe, and Eric S. Rosengren, 1997, How Well Capitalized are Well-Capitalized banks, New England Economic Review 19, 41-51.

Pohlman, John T., and Dennis W. Leitner, 2003, A comparison of Ordinary Least Squares and Logistic Regression, The Ohio Journal of Science, v103, n5, 118-125.

Ronn, Ehud I., and Avinash K. Verma, 1986, Pricing Risk-Adjusted Deposit Insurance: An Option-Based Model, The Journal of Finance 41.4, 871-896.

Sarma, Mandira, 2007, Understanding Basel Norms, Economic and Political Weekly, 42 No. 33, 3364-3367.

Stiroh, Kevin J., 2006, New Evidence on the Determinants of Bank Risk, Journal of Financial Services Research 30.3, 237-263.

Stiroh, Kevin J., and Adrienne Rumble, 2006, The Dark Side of Diversification: The Case of U.S. Financial Holding Companies, Journal of Banking & Finance 30, Issue 8, pp. 2131-2161.

Duan, Jin-Chuan, and Min-Teh. Yu, 1994, Assessing the Cost of Taiwan's Deposit Insurance, Pacific-Basin Finance Journal, 2, 73-90.

Monographs

Berk, Jonathan and Peter DeMarzo, 2007, Corporate Finance, Second Edition, © 2011, 2007, Pearson Education, Inc., publishing as Prentice Hall, 75 Arlington Street, Boston, MA 02116, pp. 80-82, 293-295.

Hanousek, Jan, and Gerard Roland, 2001, Banking Passivity And Regulatory Failure In Emerging Markets: Theory And Evidence From The Czech Republic, William Davidson Working Papers.

Peresetsky, Anatoly, Alexander Karminsky, and S. V. Golovan, 2007, Russian Banks' Private Deposit Interest Rates and Market Discipline, BOFIT Discussion Papers.

Governmental

Financial Supervisory Authority of Sweden, 2013, Promemoria - Riskviktsgolv för svenska bolån, FI Dnr 12-11920.

Finanskriskommittén, SOU 2013:6, Swedish National Debt Office.

Heikensten, Lars and Kerstin Alm, 2005, Reformerat system för Insättningsgarantin, SOU 2005:16, Department of Finance.

Labonte, Marc, 2013, Systemically Important or ”Too Big to Fail” Financial Institutions, Congressional Research Service, 7-5700.

Nygren, Pär and Ann-Christine Hagelin, 2007, En modell med riskavspeglande avgifter för insättningsgarantin, Dnr 2007/1600, Swedish National Debt Office.

Magazines, Newspapers and Speeches

Borg, Anders, 2011, Vi måste stärka skyddet mot skuldkrisen ytterligare, Dagens Nyheter, Aug 16.

Haldane, Andrew G., and Vasileios Madouros, 2012, "The dog and the Frisbee." Speech presented at the Federal Reserve Bank of Kansas City’s Jackson Hole Economic Policy Symposium.

Magnusson, Niklas, 2013, Sweden Teaches Bank Crisis Prevention to Top Basel Rules, Feb 19

University Papers

Acharya, Viral, Lasse H. Pedersen,Thomas Philippon, and Matthew Richardson, 2010, Measuring Systemic Risk, Working Paper 10-02, New York University, Stern School of Business.

Flaherty, Michael, 2013, Too Small to Forget: An Analysis of the Changing Banking Industry and the Continuing Importance of Smaller Institutions, Honors Scholar Theses, Paper 288, University of Connecticut.

Tudor, Alexandra, 2010, Income Smoothing and Earnings Informativeness, Erasmus MC: University Medical Center Rotterdam

Institutes

Acharya, Viral, Philipp Schnabl and Gustavo Suarez, 2011, Robust Capital Regulation. No. 490. Staff Report, Federal Reserve Bank of New York.

Altunbas, Yener, Simone Manganelli, and David Marques-Ibanez, 2011, Bank Risk During the Financial Crisis: Do Business Models Matter?, No. 1394. European Central Bank.

Amato, Jeffrey and Craig Furfine, 2003, Are Credit Ratings Procyclical?, BIS Working Paper No 12.

Anderson, Nick, and James Chappell, 2013, European Banks, Capital: misunderstood, misused and misplaced, Berenberg Equity Research.

Bank for International Settlements, 2005, An Explanatory Note on the Basel II IRB Risk Weight Functions.

Bank for International Settlements, 2013, A Brief History of the Basel Committee.

Basel Committee on Banking Supervision, 1988, International Convergence of Capital Measurement and Capital Standards, Basel, July.

Das, Sonali, and Amadou Sy, 2012, How Risky are Banks' Risk Weighted Assets?: Evidence from the Financial Crisis. No. 12/36, International Monetary Fund.

Deutsche Bundesbank, 2006, Ergebnisse Deutscher Banken im Rahmen der fünften Auswirkungsstudie (QIS 5) zu Basel II, May.

Evanoff, Douglas Darrell, and Larry D. Wall., 2000, Subordinated Debt and Bank Capital Reform No. WP-00-7, Federal Reserve Bank of Chicago.

Federal Deposit Insurance Corporation, 2000, Options Paper August 2000. Available from URL: http://www.fdic.gov/deposit/insurance/initiative/OptionPaper.html

Gonzales-Hermosillo, Brenda, 1999. Determinants of Ex-ante Banking System Distress: A Macro–Micro Empirical Exploration, Working Paper 99/33, IMF.

Köhler, Matthias, 2012, Which banks are more risky? The Impact of Loan Growth and Business Model on Bank Risk-Taking, Deutsche Bundesbank No. 33/2012 Discussion Paper.

Laeven, Luc, 2002b, Pricing of Deposit Insurance, World Bank Policy Research Working Paper 2871, The World Bank, Financial Sector Strategy and Policy Department

Le Leslé, Vanessa, and Sofiya Avramova, 2012, Revisiting Risk-weighted Assets: Why Do RWAs Differ Across Countries and What Can be Done About It?, International Monetary Fund.

Nilsson, Christian, 2012, Bank- and finance statistics 2012, Swedish Bankers' Association.

Packer, Frank and Nikola Tarashev, 2011, Rating Methodologies for Banks, BIS Quarterly Review, June.

Data

Federal Deposit Insurance Corporation, 1992-2013, Statistics on Depository Institutions (see FDIC URLs below).

Electronic Sources, retrieved 1st of April 2014

FDIC

FDIC (Ref # 1)
http://www.fdic.gov/bank/statistical/guide/index.html

FDIC (Ref # 2)
http://research.fdic.gov/bankfind/

FDIC (Ref # 3)
http://www.fdic.gov/bank/individual/failed/banklist.html

FDIC (Ref # 4)
http://www2.fdic.gov/idasp/warp_download_all.asp

FDIC (Ref # 5)
http://www2.fdic.gov/sdi/download_large_list_outside.asp

Federeal Reserve Bank of San Fransisco, retrieved 3rd of June 2014

FRBSF (Ref # 1)
http://www.frbsf.org/education/publications/doctorecon/2006/november/commercial-banks-regulation

Investopedia, retrieved 5th of May 2014

Investopedia (Ref # 1)
http://www.investopedia.com/terms/b/businessrisk.asp

Regressions, retrieved 8th of May 2014

Regressions (Ref # 1)
http://www.ats.ucla.edu/stat/stata/webbooks/reg/chapter2/statareg2.htm

Regressions (Ref # 2)
http://www.shrs.uq.edu.au/docs/intranet/StataWorkshop_5.pdf

Regressions (Ref # 3)
http://www.stata.com/manuals13/rlinktest.pdf

Regressions (Ref # 4)
http://www.stata.com/support/faqs/statistics/completely-determined-in-logistic-regression/

Regressions (Ref # 5)
http://sydney.edu.au/vetscience/biostat/macros/logistic_tut_intro.shtml

Riksgälden, retrieved 5th of May 2014

Riksgälden (Ref # 1)

https://www.riksgalden.se/sv/Insattningsgarantin/Om_Insattningsgarantin/Historik/

Riksgälden (Ref # 2)

https://www.riksgalden.se/sv/omriksgalden/Bankstod/Stod-till-banker-i-kris/Stabilitetsfonden/

Swedish Bankers' Association, retrieved 5th May 2014

Swedish Bankers (Ref # 1)
http://www.swedishbankers.se/web/bf.nsf/$all/03C87A40933FEB85C12576180046A87C

Swedish Bankers (Ref # 2)
http://www.swedishbankers.se/web/bf.nsf/$all/B8C74984FDFD9FF1C1257620003AE16C

Swedish Bankers (Ref # 3)
http://www.swedishbankers.se/web/bf.nsf/$all/0B450AE7C2DC4B14C1257620003BB5EB?open

Swedish Bankers (Ref # 4)
http://www.swedishbankers.se/web/bf.nsf/$all/3EB3F41103785D17C12576180044EBF3

Swedish Bankers (Ref # 5)

Legal

Lag (1995:1571) om insättningsgaranti 1 Chapter 12- 14 §

Lag (1995:1571) om insättningsgaranti 1 Chapter 8 §

Lag (1995:1571) om insättningsgaranti, 1 Chapter 12 §

Lag (2006:1371) om kapitaltäckning och stora exponeringar 4 Chapter 7 §

Lag (2008:814) om statligt stöd till kreditinstitut, 1 Chapter 2 §

Appendix

Reservations

We must reserve a critical perspective of the all the data we get and try to understand the motives of all actors affected by the deposit insurance fee. This section provides a short overview of the possible motives of important stakeholders.

Banks and financial institutions

Banks may understandably want to reduce the fees they pay for deposit insurance because higher fees will ultimately reduce money available for other spending, impacting negatively the rate of return. Thus, unless it is "beneficial", banks that could be subject for a fee raise would want to downplay the need for increasing the level of fees, most likely by claiming their assets are less risky than regulators or other stakeholders claim.

Regulators

In many countries there is an intricate relationship between the biggest banks and the government as a result from the important roles of the banks as well as from their effect on the countries' financial stability. This warrants rigorous governmental oversight with the motivation that the banks are too important i.e. "too big to fail" without causing instability. In order to create some margins (and protect the economic stability) in the event of a severe negative impact on a bank or some banks financial positions, the government would seek to increase the level of RWA and deposit insurance fees, making the banks hold extra capital to meet capital and liquidity requirements. There are also other considerations for governments, depending on the country. Some governments might have a specific agenda of showing prudent financial stewardship. By setting high standards for banks, the may want to prove they are a prudent and safe government (Borg, 2011). Specifically, they may want to avoid blame for being reckless. They do not want to have insisted on lower standards when a negative shock comes. Others might not want to stimulate the economy, as in much of Europe today. It might therefore be in their interest to delay harsher standards so as not to be procyclical. Thus governments have incentives both to raise and not to raise fees.

Central banks

Central banks have the assignment to run a country's monetary policy. Part of this includes setting some key interest rates that will affect the market rates banks and

other financial institutions use to lend money between themselves and to customers. Higher interest rates would, ceteris paribus, make it more profitable for banks to lend money to customers if they at the same time can keep their costs unchanged (i.e. increased margins). A demand by outsiders to increase the level of fees will impose higher costs on the banks, leading to decreased margins. Lowering key interest rates should stimulate the economy, as it will be cheaper to access debt capital. On the other hand, the banks may find it difficult to maintain their ordinary margins if at the same time demands for substantially higher fees make their costs rise. As such, banks might not be willing to lend money to the same extent as otherwise, creating a mismatch between supply and demand of debt capital.

NGOs

Organizations such as the IMF work on a global scale and have to juggle the different needs of different countries with respect to, among other things, financial stability, economic growth and trade. Is this environment, it is not difficult to see that conflicts of interest between countries and their institutions and bank corporations could strain the efforts of these organizations. While they need to promote some kind of objective stance in order to maintain credibility, it must be carefully designed so as to keep relationships with the NGO and governments/banks open. We must remember that the NGO would not be able to exist without the mutual interests of its member countries.

Unions

Unions want to secure the positions and competitiveness of the employees. If a company is doing well, the unions can use this as leverage to demand e.g. pay raises or to negotiate better employee deals such as insurance policies or vacation allowances. One can assume that there is a direct interest from the unions to increase the value of the companies for which their members work to obtain a stronger negotiating position. Following the same logic, an increased fee level that takes away profitable investment opportunities for a bank will harm the position of its staff and by that also the position of the unions. Not to forget though is that unions usually and especially in Sweden, have a widespread member structure and so will need to take into account not only the position of their members in banks but also their members in other professions. They must recognize that keeping the financial system in check may provide long-term benefits for the society as a whole,

even though some banks might not be able to become as profitable or "big" as they potentially could.

Academia

Ideally, academia should be independent of any company or institutional pressures when conducting research. However, of course, academia often has its own interests and positions. Thus, academics might find it convenient to argue for a view that fits with other theories of their own, or to make their findings more interesting by choosing data in a way that makes their conclusion look more clear and motivated. Generally, papers that seem to prove something are easier to get published, and therefore it is often wise to keep this in mind when reading "sensational" papers.

Definitions of Capital

Tier 1 (core) capital under Basel III consists of equity capital and published reserves from post-tax retained earnings (paid up capital + statutory reserves + disclosed free reserves) - (minority interests + equity investments in subsidiaries engaged in banking and financial activities +deferred tax assets + goodwill + current and b/f losses) (from Basel Committee on Banking Supervision, 1988).

Tier 2 (supplementary) capital under Basel III (limited to 100% of Tier 1 capital) consists of undisclosed reserves + revaluation reserves + general provisions/general loan-loss reserves + hybrid debt capital instruments + subordinated term debt (limited to 50% of Tier 1 capital) (from Basel Committee on Banking Supervision, 1988).

Swedish Fee Model Calculation

Fee model formula

$$U(z) = a + bexp(-cz)$$

Where z signifies the CAR, $U(z)$ signifies the distribution value that the function generates, c is a parameter determining curvature, a is a parameter determining the convergence point and b is a parameter used to make sure all conditions are fulfilled. Conditions are: the distribution value can at most be 1.0, which happens when the CAR is at the lower limit of 8%. It can at least be equal to a, which happens when the CAR is very high. The parameter b has the only task to make sure both of the previously mentioned conditions are fulfilled.

Steps

1) Determine the values on a and c and calculate b according to the specification:

$$b = (1 - a)/exp\ (-c * 8)^{43}$$

and enter these values into the function U(z).

2) Calculate distribution values as described above using the function $U(z)$.

3) $Preliminary\ fee = U(z) * fee\ percent * guaranteed\ deposits\ of\ institution$

4) If the CARs of all affiliated banks are equal to 8%, the sum of all the banks' fees would be the same as the fee percent multiplied by the total amount of guaranteed deposits in the system.

5) Unless there is a state as described in 4), the fee to be paid is calculated as follows:

$$fee = preliminary\ fee * \left(fee\ percent * \frac{total\ guaranteed\ deposits}{\sum preliminary\ fees}\right)$$

6) $$fee\ in\ \% = \left(\frac{fee}{guaranteed\ deposits\ of\ institution}\right) * 100$$

7) If any institution's fee is above or below the target interval of 0.6 to 1.4, those fees will need to be adjusted either upwards or downwards so that they in the end fall within the target interval. This means that the fees of the other institutions must also be adjusted in order for the total of the feel to be equal to the yearly fixed base.

[43] Provided that the system has set a CAR of 8% as the lower limit. Otherwise the 8 is exchanged for any other limit of choice. The current model uses 8%.

In the case of the fee for the institution falls *below* the lower limit of the target interval:

$$\left(\frac{fee\ in\ \% - lower\ limit\ of\ target\ interval}{100}\right) * guaranteed\ deposits\ of\ institution$$

In case of the fee for the institution falls *above* the upper limit of the target interval:

$$\left(\frac{fee\ in\ \% - upper\ limit\ of\ targer\ interval}{100}\right) * guaranteed\ deposits\ of\ institution$$

8) The next step is to sum the so-called surplus and deficit values obtained in 7) and get a net value (or error net) for those fees that fell outside of the target interval.

9) To make the sum of all fees to equal the yearly fixed base the error net needs to be proportionately spread across the fees of the institutions that ended up *inside* the target interval. The final fees of the institutions within the target interval are calculated as:

$$final\ fee = fee + error\ net * \left(\frac{fee}{\sum fees\ of\ institutions\ within\ target\ interval}\right)$$

For the institutions that ended up outside the target interval the final fees are calculated as:

$$final\ fee = \left(\frac{\left(fee\ in\ \% - \left(\frac{surplus\ or\ deficit\ value\ for\ institution}{guaranteed\ deposits\ of\ institution}\right) * 100 * guaranteed\ deposits\ of\ institution\right)}{100}\right)$$

10) $$final\ fee\ in\ \% = \left(\frac{final\ fee}{guaranteed\ deposits\ of\ institution}\right) * 100$$

FDIC Data Files

From http://www2.fdic.gov/SDI/download_large_list_outside.asp we download All_Reports_19921231.zip to All_Reports_20130930.zip

Each such report contains a set of sub files focusing on a specific area. As we extract our own variables from more than 200 different such sub-files, we have to write macros in Excel to handle the data and to remove incomplete observations. Often, the resulting Excel sheets in which we collect data become too large for Excel to handle properly and we have to divide our data into many smaller files to allow for Excel to function.

From the All Reports large zipped files, we use especially *Assets and Liabilities*, *Income and Expense*, *Net Loans and Leases*, *Total Deposits* and *Total Interest Expenses.* The files are used to create the data required for our regressions, *Assets and Liabilities* mainly for building and testing the current Swedish fees model and the other files mainly to create alternative variables.

We use standard FDIC names for the data. See *IDAllDefinitions*, contained in the FDIC large zipped downloadable files.

Parameter Sources and Build

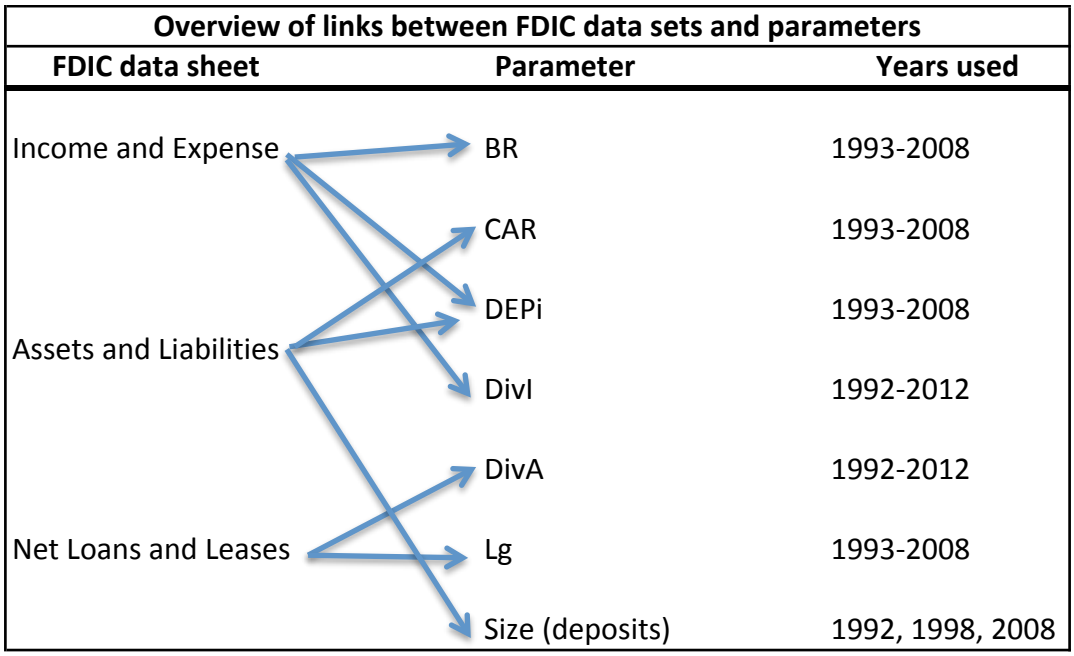


Figure A1. The graph describes from which FDIC raw data sheet each parameter has been built and from what time period data have been extracted. Most parameters derive information from multiple sheets, whereby it has been necessary to correctly link bank-specific information between sheets.

BR

The business risk variable is based on the Income and Expense sources from FDIC. Simply put, it tracks the relative standard deviation of net income (*netinc*) over a period of time. That is, the period standard deviation of net income divided by the average net income for the period. Data are assigned to bank *certs* using the Excel function Vlookup(). Since we use five-year average business risk estimations with relative standard deviation of net income over the five years we only use banks for which we have five consecutive years of data (1993-1998 for 1998 tests and 2003-2008 for 2008 tests), removing other banks. For the long-term BR measure, we use banks that remain in the data from 1993 to 2008 and estimate average BR over the entire period.

$$BR = \frac{avg(StDev(netinc))}{avg(netinc)}$$

CAR

From the Assets and Liabilities data, we construct a CAR variable for all banks. Then we construct a modified CAR variable, which has a value of 8% as its minimum to take into account the fact that this is the limit allowed by the Basel rules and the

minimum set by the current Swedish fee model. We construct a bracket category variable by using the Excel rank function to rank banks by their CARs.

$$CAR = \frac{(rbct1 + rbct2)}{rwaj}$$

We further use *dep* and *depi* for all banks to create a *depi* percentage variable, showing how many percent of a bank's deposits are covered by the FDIC. We have to expand these backwards to times when no data exist for *depi*, and to banks which the FDIC does not estimate *depi*, by applying a formula set to generate estimated *depi* percentages for years with no such data primarily based on future data for the same bank, and, if this is not available, on an average for all banks.

Simulated Swedish fees are then added according to the real model procedure as well as data for bank failures, failures for certain years and the number of failures (FDIC insured defaulting banks).

For a detailed list of original, intermediate and output variables, see Model Data Guide Excel Sheet.

DEPi

DEPi data comes from Total Interest Expenses and Total Deposits. *edepdom* (interest expense) from Total Deposits is divided by *depdom* (total deposits held) from Total Deposits to get a return on deposits (DEPi).

$$DEPi = \frac{edepdom}{depdom}$$

This is assigned to banks and years with large Vlookup() tables, based on all *certs*. All unique bank certs are listed and specific year data brought into columns with Vlookup(). We remove banks for which data is insufficient. The data appears in like this in Excel.

cert2008	depdom2008	edepdom2008	ReturnDep2008
14	37159163	217886	0.005863587
35	551699	15075	0.027324682

DivI

DivI is made up data from Income and Expense. It builds on a function looking at the proportion of income types to total income (revenue). Here, the categories are *Interest income* (*intinc*), *Noninterest Income* (*nonii*), *Gross fiduciary activities* (*ifiduc*), *Service Charges* (*iserchg*), *Trading account* (*igltrad*) and *Additional Income* (*idothnii*),

shown below as proportions of total. For each bank and data period, we looked at how data were divided into the above "DivI categories". Below we have data for an example bank, cert 15448, for the 4th quarter of 1995.

cert2003.1	TOTAL	Interest income	Noninterest income	Fiduciary activities	income
9	8023	0.614109435	0.192945282	0.039262121	

Service charges, deposits	Trading account	Add. Noninterest Inc.	Control	DivI
0.032531472	0	0.121151689	1.0000	0.431635823

$$DivI = \frac{(intinc^2 + nonii^2 + ifiduc^2 + iserchg^2 + igltrad^2 + idothnii^2)}{Total\ income^2}$$

The diversification measure will yield a value between 1 and 0. Values are then removed where income categories do not exist and Vlookup() is used to construct tables with many time periods.

DivA

Diversification of Assets/Loans is based on the Net Loans and Leases data. It is constructed by looking at the proportion of different categories of loans to the total loan portfolio.

Specifically, we create five broad categories of loans, based on several smaller ones of similar nature. The ones we create are listed below in italics, with the corresponding FDIC data in parenthesis. The first four are based on real estate: *Real Estate* (*lnre*) and its subcategories *Commercial* (*lnrecons + lnrenres*), *Family Housing* (*lnremult + lnreres*), *Farm Real Estate* (*lnreag*). The second group of four consists of non-mortgage loans: *Farm Loans* (*lnag*), *Industrial and Commercial Loans* (*Inci*), *Personal Loans* (*lncon*) and *Public Sector Loans* (*lnotci*). These categories cover all main loan categories the FDIC specifies.

For each bank and data period, we looked at how data were divided into the above "DivA categories". Below we have data for an example bank, cert 15448.

cert	Total	Real Estate Total	Commerc. (R.E. secured)	Family Housing	Farm R. E.
9	**371191**	**0.915485559**	0.229130017	0.685016609	0.001338933

Farm Loans	Commerc. & Ind.	Personal Loans	Public Sector & Other	CONTROL	DivA
0.020517739	**0.034707199**	**0.023508113**	**0.005784084**	1.00	**0.840325462**

We decided to treat all real estate assets as a single category, Real Estate here. Note that the other real estate categories together are the same as Real Estate – because *lnre* is made up by *lnreonc*, *lnrenres, lremult, lnreres* and *lnreag*. Thus we get five main categories of loans. The DivA measure then is calculated as the square of all the categories' proportion of the total. We thus get

$$DivA = \frac{(RE^2 + FL^2 + C^2 + P^2 + P\&O^2)}{Total\ Loans^2}$$

The diversification measure will yield a value between 1 and 0. Values are then removed where income categories do not exist and Vlookup() is used to construct tables with many time periods.

Lg

The loan growth variable builds on data from Net Loans and Leases. It tracks the total size of outstanding loans (the same as the amount of assets in DivA). This is tracked over five years in the test case, to establish the geometric average annual growth rate. Lg is estimated over five-year periods, 1993-1998 for 1998 tests and 2003-2008 for 2008 tests. The long-term Lg measure uses data from 1993-2008 to test on 2008 data and includes only banks that have observations for each of these years. Banks that default during the period or are missing data for other reasons will be left out of the estimation. The following is the equation used. Note that *n* is the number of years over which the estimation period runs (five years for 1998 and 2008 standard tests, 15 years for the long-term test).

$$Lg = \left(\frac{Loans_{YearX}}{Loans_{YearX-n}}\right)^{\left(\frac{1}{n}\right)} - 1$$

The outcome appears like this in Excel:

cert	1998	1993	Geometrical LG
8	1731936	1685087	0.0054996
9	116987	82077	0.073453474
14	6973280	2698085	0.209139184

Banks in Sweden

Summary information on banks in Sweden, table 1[44]

Type of Bank	2000 (Dec)	2012 (Dec)
Swedish commercial banks	22	37
-of which four big banks	4	4
-of which former savings banks	9	14
-of which other Swedish commercial banks	9	19
Foregin banks	21	29
-of which subsidiaries	2	2
-of which branches	19	27
Savings banks	79	49
Co-operative banks	2	2
TOTAL	**124**	**117**

Table A1. The table describes the Swedish banking system in terms of the number of banks split on for instance commercial and foreign banks, and so on. Comparison is between the years 2000 and 2012.

Summary information on banks in Sweden, table 2[45]

Year	Operating profits (1)	of which dividends from group companies	Loan losses (2)	Balance sheet total
1992	-38 546	-	57 571	1 518 644
1993	-16 122	-	46 427	1 454 643
1994	12 225	-	14 637	1 456 708
1995	18 520	-	9 070	1 584 983
1996	23 976	2 367	4 790	1 861 635
1997	15 852	6 042	4 631	2 145 194
1998	23 082	13 675	3 696	2 410 481
1999	18 377	10 291	421	2 466 718
2000	25 905	6 392	1 265	2 883 511
2001	29 572	5 284	3 257	3 145 393
2002	15 074	5 741	3 603	3 288 175
2003	22 276	8 582	2 641	3 290 634
2004	36 836	21 078	1 565	3 879 110
2005	27 053	9 643	1 178	4 539 904
2006	73 911	48 625	341	5 088 692
2007	49 566	25 159	984	6 026 259
2008	42 140	24 335	9 139	7 384 539
2009	37 042	17 122	13 227	6 917 147
2010	51 323	28 250	4 329	6 919 515
2011	57 470	28 956	4 192	7 542 725

All banks that have operated in Sweden during the year and are under the supervision of the Swedish Financial Supervisory Authority (Finansinspektionen). Also included are foreign owned bank branches operating in Sweden. Swedish credit compaines' branches abroad are also included.
(1) After loan losses
(2) Net loan losses

Source: Statistics Sweden, Financial Enterprises

Table A2. The table describes the Swedish banking system in terms of monetary values, such as aggregate operating profits and balance sheet totals. Annually between 1992 and 2011.

[44] Swedish Bankers (Ref # 5)
[45] Nilsson (2012)

Descriptive Testing Appendix

Income composition development

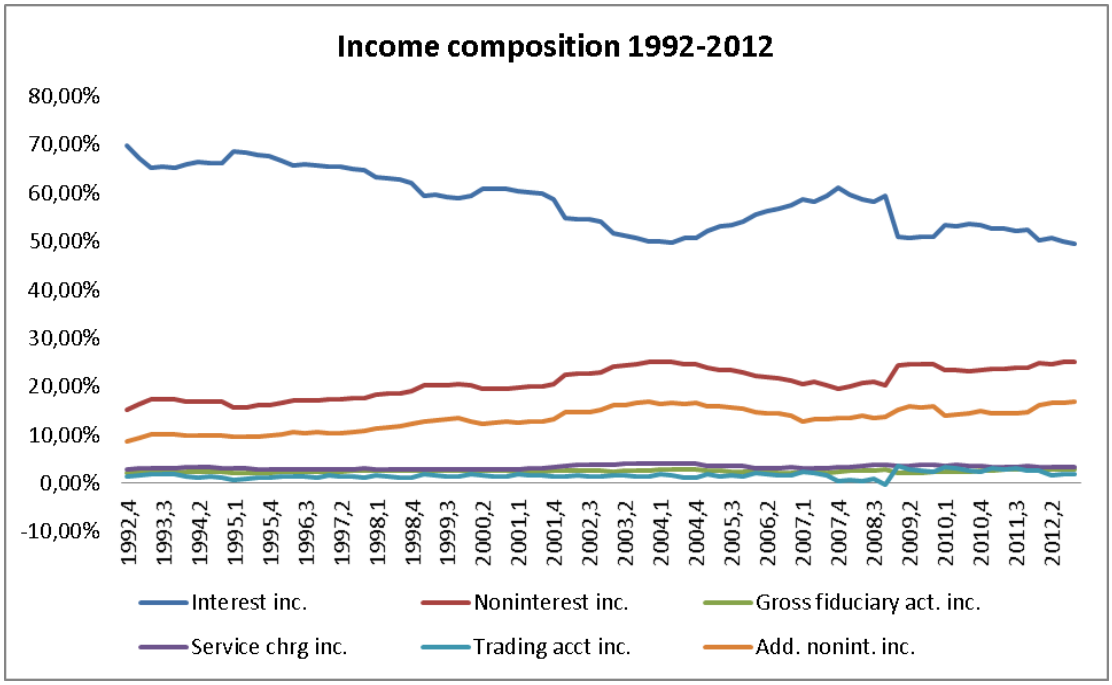


Figure A2. The graph describes the change in composition of income-generating items derived from the P&Ls of all FDIC certified banks at each point of measurement (quarterly) between 1992 and 2012.

Loan portfolio composition development

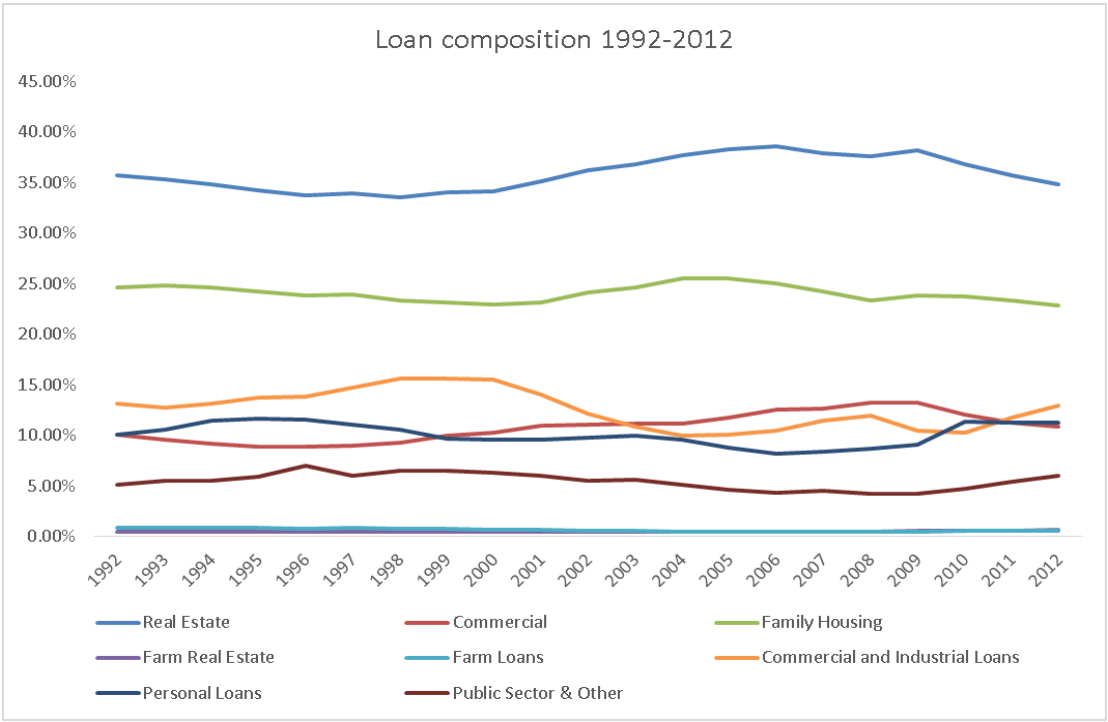


Figure A3. The graph describes the development of composition of the aggregate loan portfolio (loans and leases)-derived from the balance sheets of all FDIC certified banks at each point of measurement (annually) between 1992 and 2012.

Over-time graphs

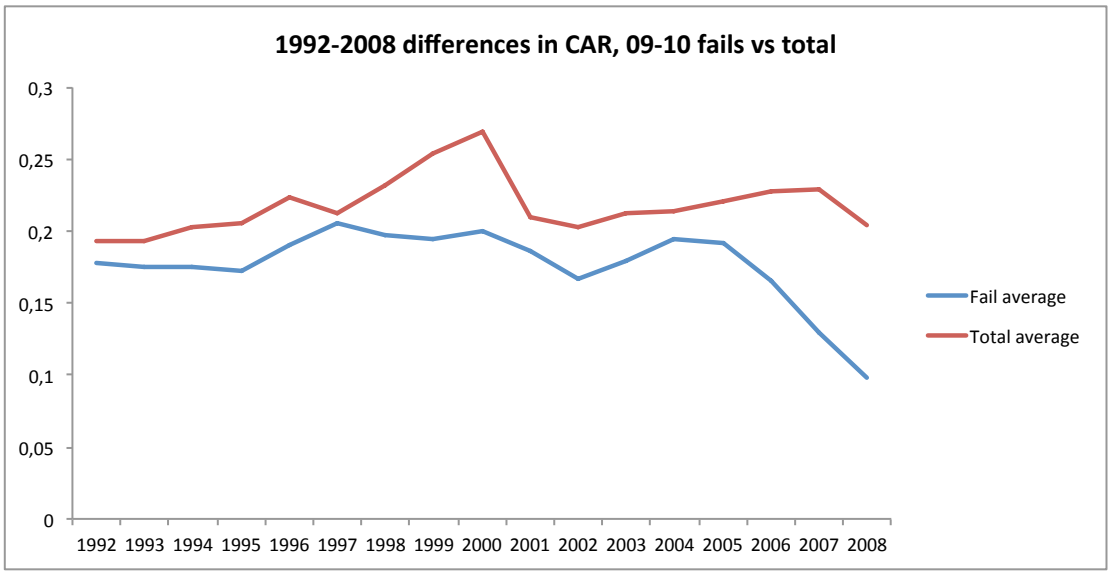


Figure A4. The graph displays the development of the average CAR between 1992 and 2008, measured annually. The CAR measure is split between the subgroup of banks that failed between 2009 and 2010 and the population of FDIC insured institutions.

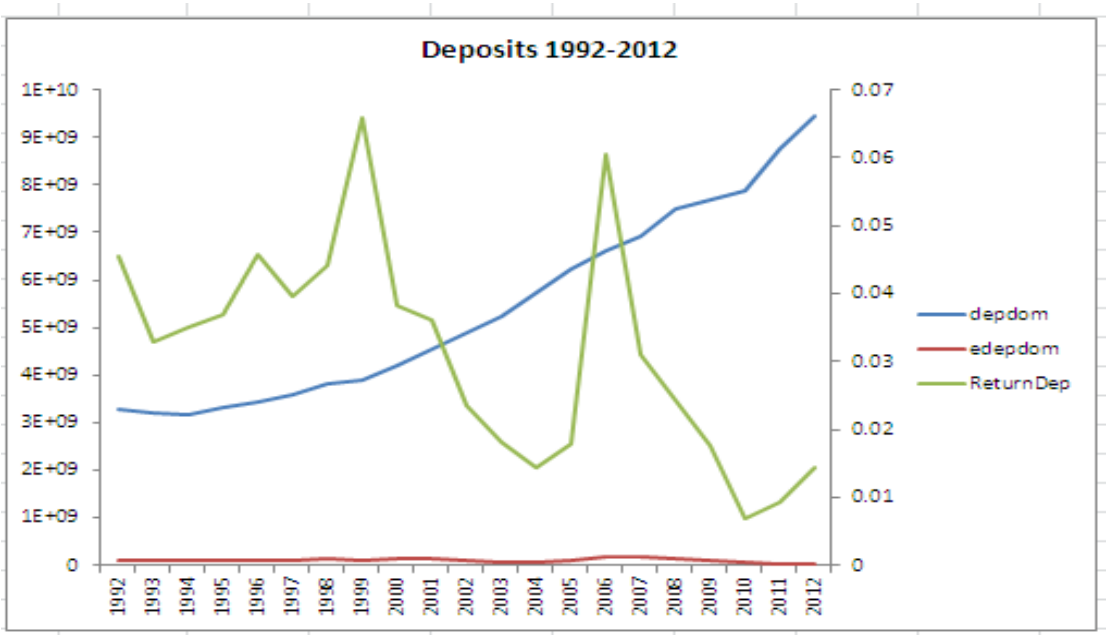


Figure A5. The graph displays the development of U.S. domestic deposits (depdom, left), banks' interest rate expenses on deposits (edepdom, left) and the average interest rate on deposits (ReturnDep, right) over the 1992-2012 period.

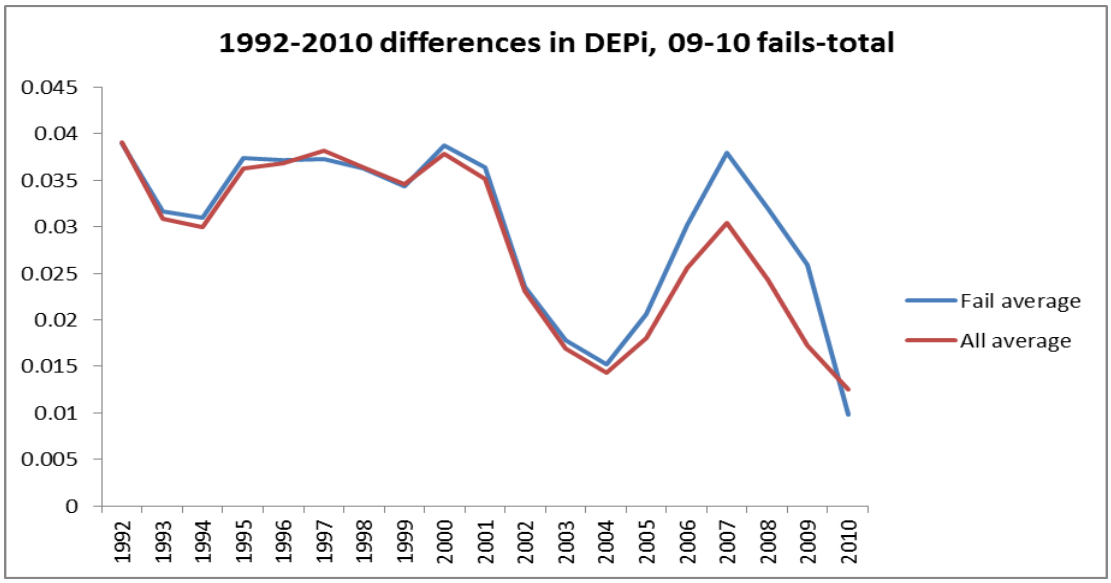


Figure A6. The graph displays the development of the average DEPi between 1992 and 2010, measured annually. The DEPi measure is split between the subgroup of banks that failed between 2009 and 2010 and the population of FDIC insured institutions.

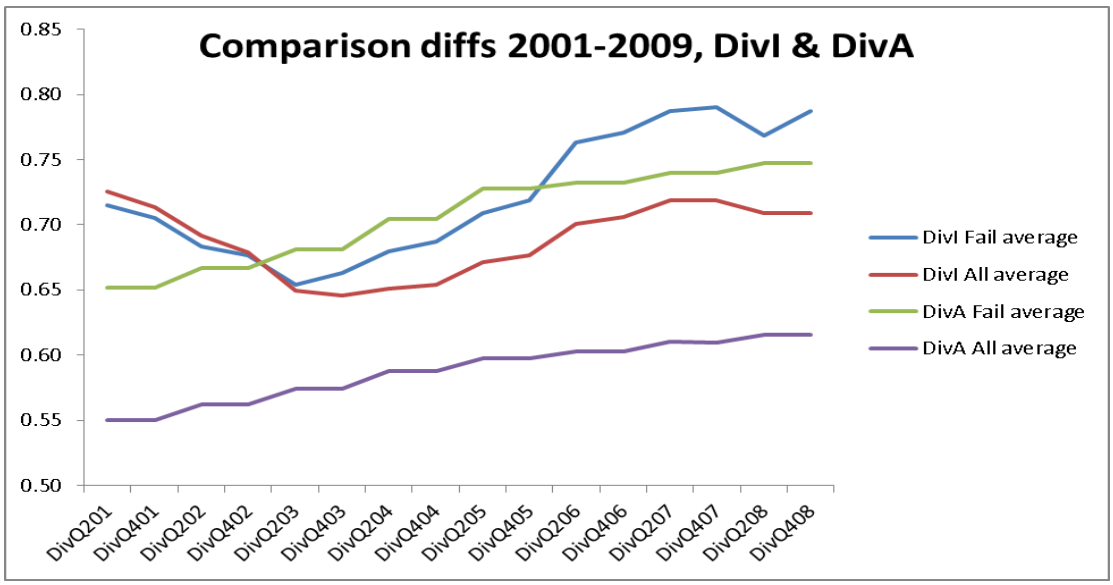


Figure A7. The graph displays the development of income (DivI) and loan (DivA) diversification between 2001 and 2009, measured quarterly. Each diversification measure is split between the subgroup of banks that failed between 2009 and 2010 and the population of FDIC insured institutions.

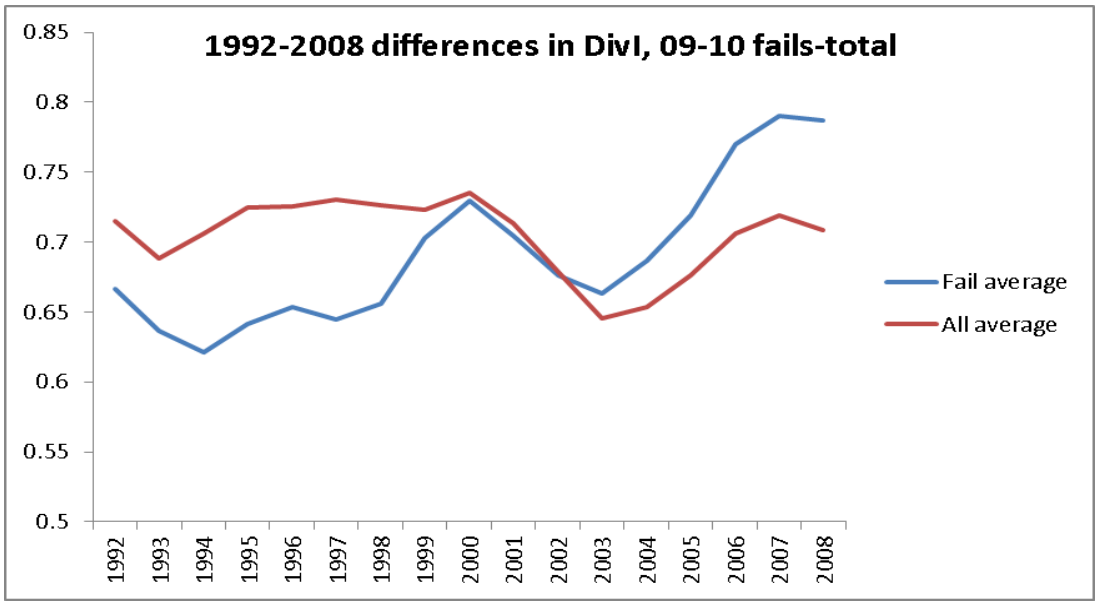


Figure A8. The graph displays the development of income (DivI) in the aggregate between 1992 and 2008, measured annually. The diversification measure is split between the subgroup of banks that failed between 2009 and 2010 and the population of FDIC insured institutions.

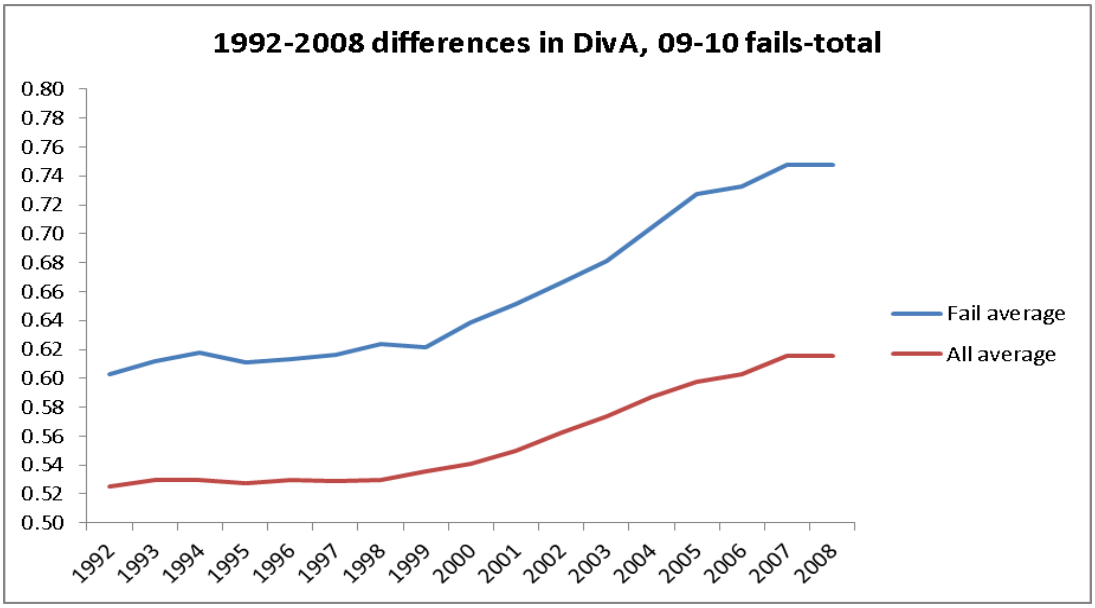


Figure A9. The graph displays the development of loans (DivA) in the aggregate between 1992 and 2008, measured annually. The diversification measure is split between the subgroup of banks that failed between 2009 and 2010 and the population of FDIC insured institutions.

Business risk measure

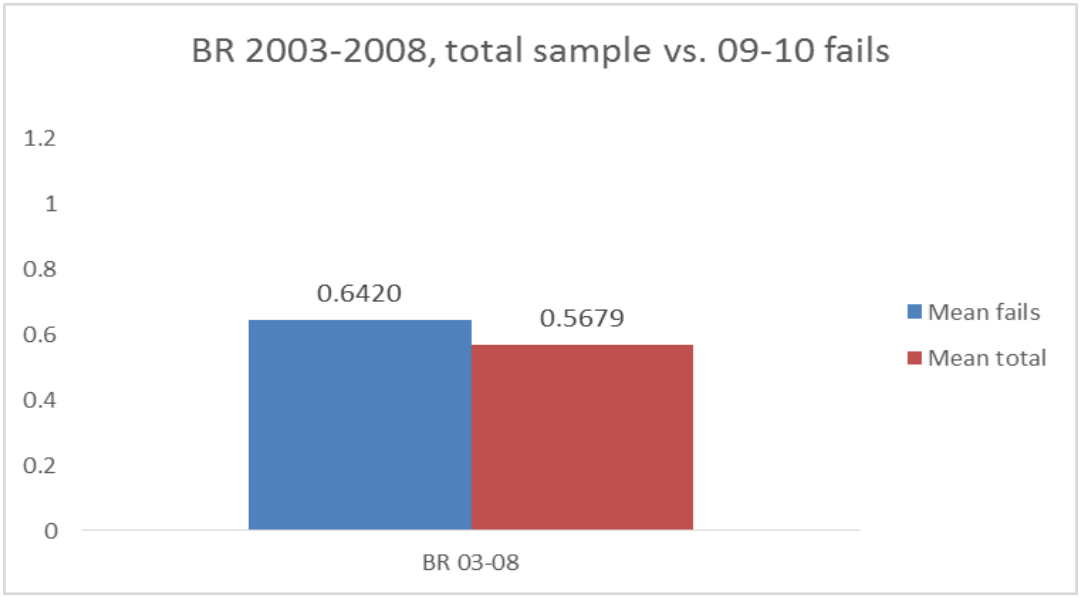


Figure A10. The chart displays the 2003-2008 BR (average net income standard deviation divided by the 2003-2008 average net income) derived from the P&Ls of all FDIC certified banks that existed over the full 2003-2008 period. The presentation is split on the subgroup of banks that defaulted between 2009 and 2010 and the population of FDIC insured institutions.

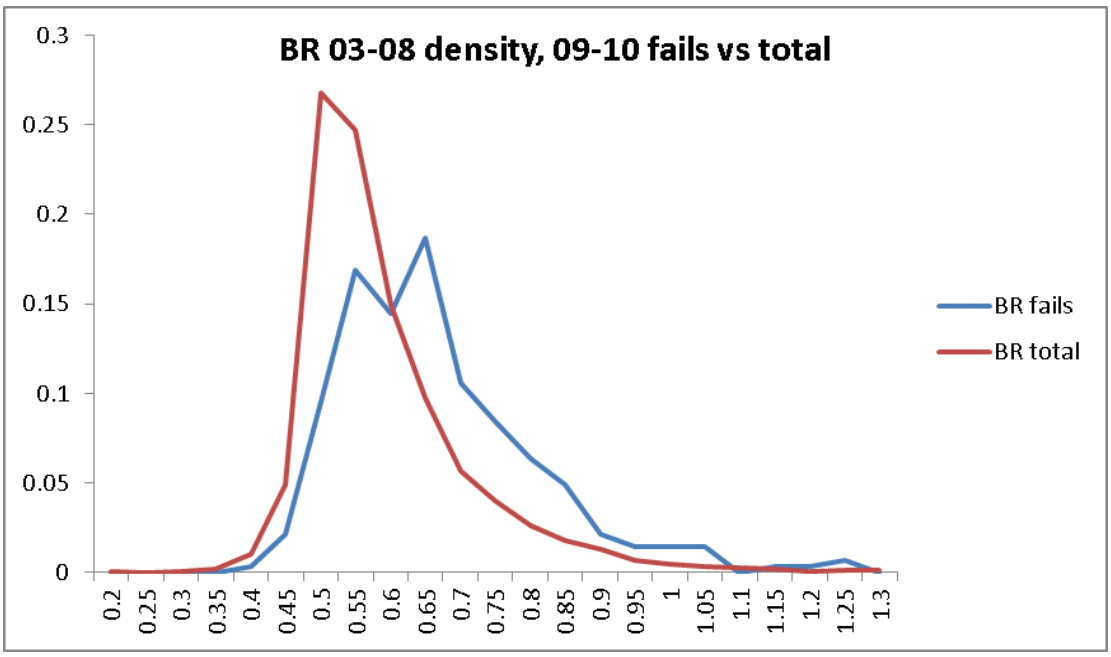


Figure A11. The chart displays the 2003-2008 BR density split by the group of default banks in 2009-2010 to the total population of FDIC insured institutions. Densities are expressed as the share of observations (y-axis) occurring at each BR magnitude (x-axis).

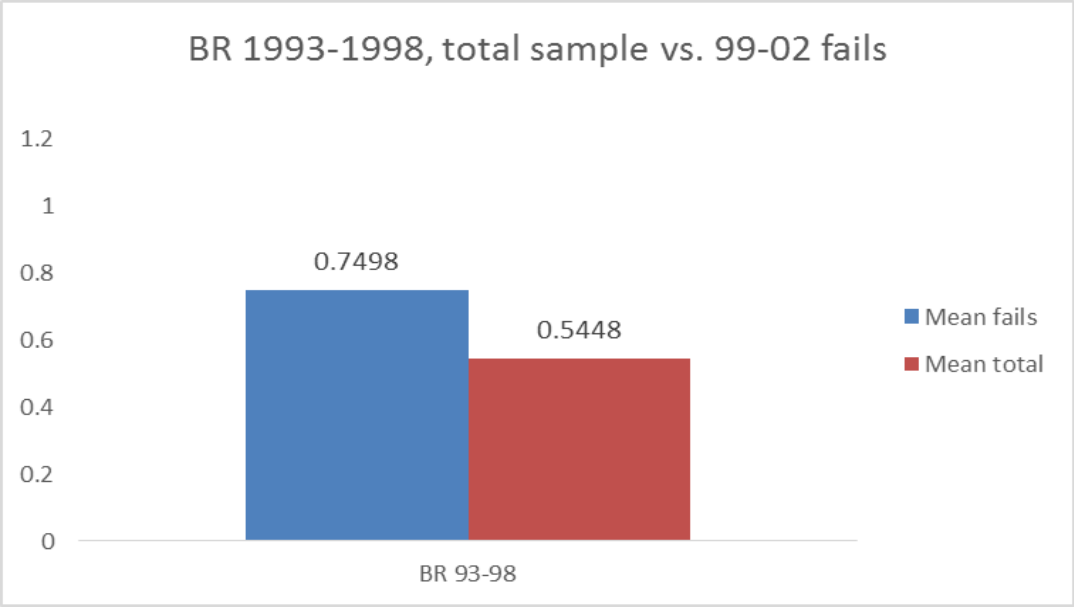


Figure A12. The chart displays the 1993-1998 BR (average net income standard deviation divided by the 1993-1998 average net income) derived from the P&Ls of all FDIC certified banks that existed over the full 1993-1998 period. The presentation is split on the subgroup of banks that defaulted between 1999 and 2002 and the population of FDIC insured institutions.

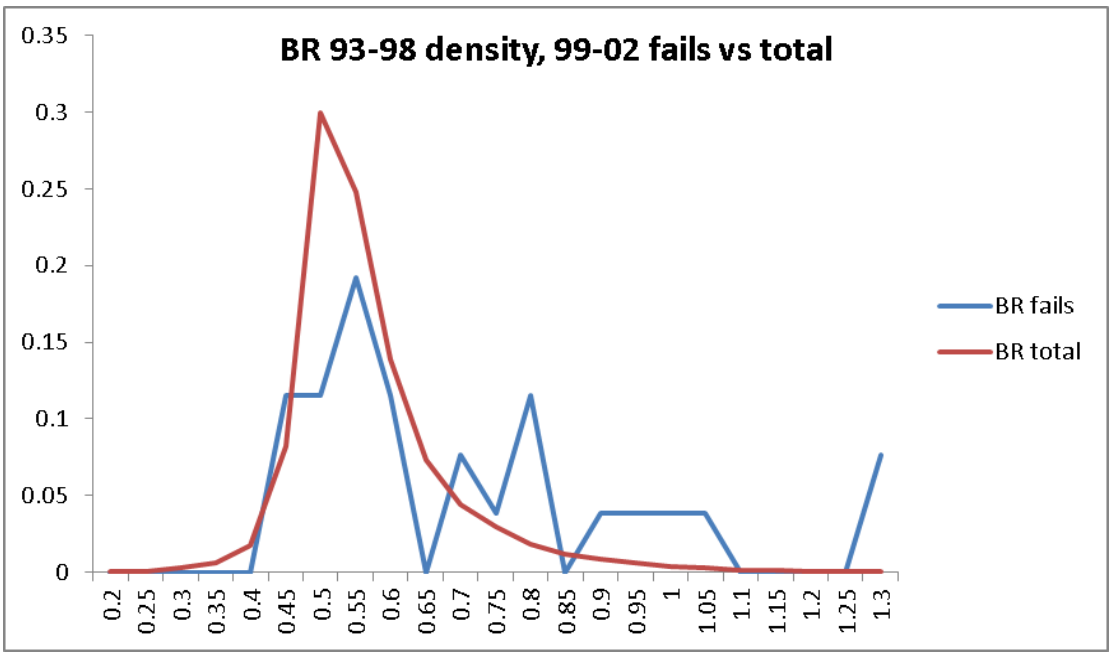


Figure A13. The chart displays the 1993-1998 BR density split by the group of default banks in 1999-2002 to the total population of FDIC insured institutions. Densities are expressed as the share of observations (y-axis) occurring at each BR magnitude (x-axis).

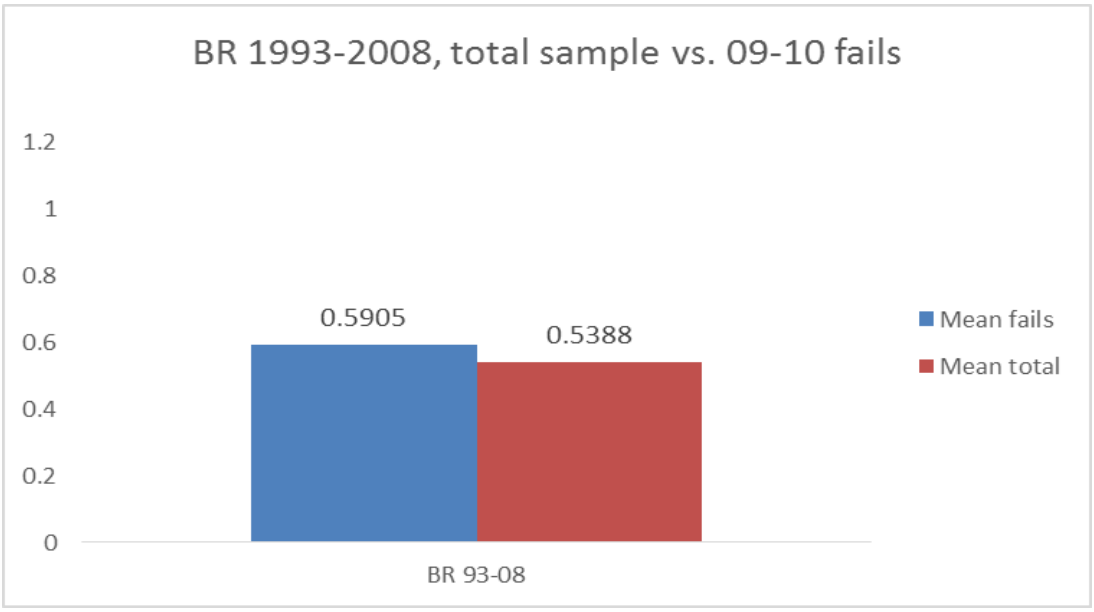


Figure A14. The chart displays the 1993-2008 BR (average net income standard deviation divided by the 1993-2008 average net income) derived from the P&Ls of all FDIC certified banks that existed over the full 1993-2008 period. The presentation is split on the subgroup of banks that defaulted between 2009 and 2010 and the population of FDIC insured institutions.

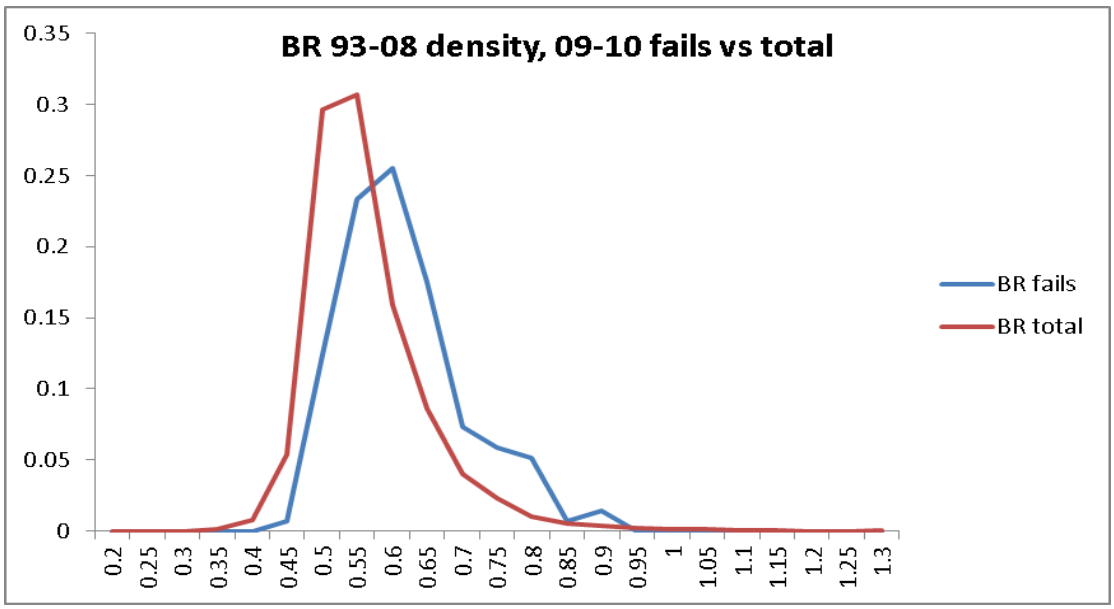


Figure A15. The chart displays the 1993-2008 BR density split by the group of default banks in 2009-2010 to the total population of FDIC insured institutions. Densities are expressed as the share of observations (y-axis) occurring at each BR magnitude (x-axis).

CAR measure

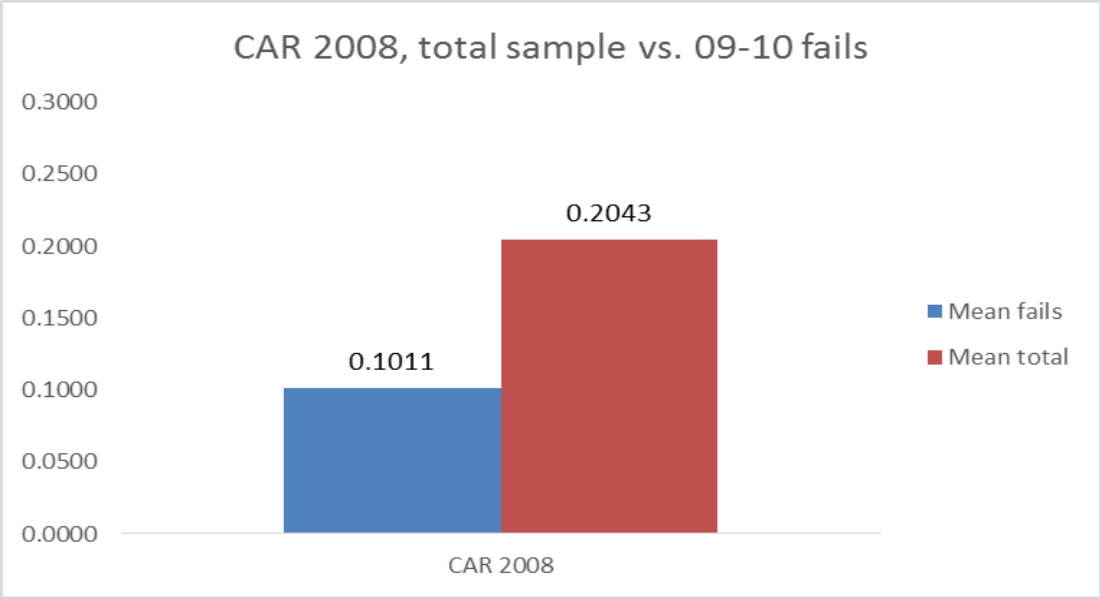


Figure A16. The chart displays the 2008 CAR (regulatory capital to risk-weighted assets), derived from the balance sheets of all FDIC certified banks that existed in 2008. The presentation is split on the subgroup of banks that defaulted between 2009 and 2010 and the population of FDIC insured institutions.

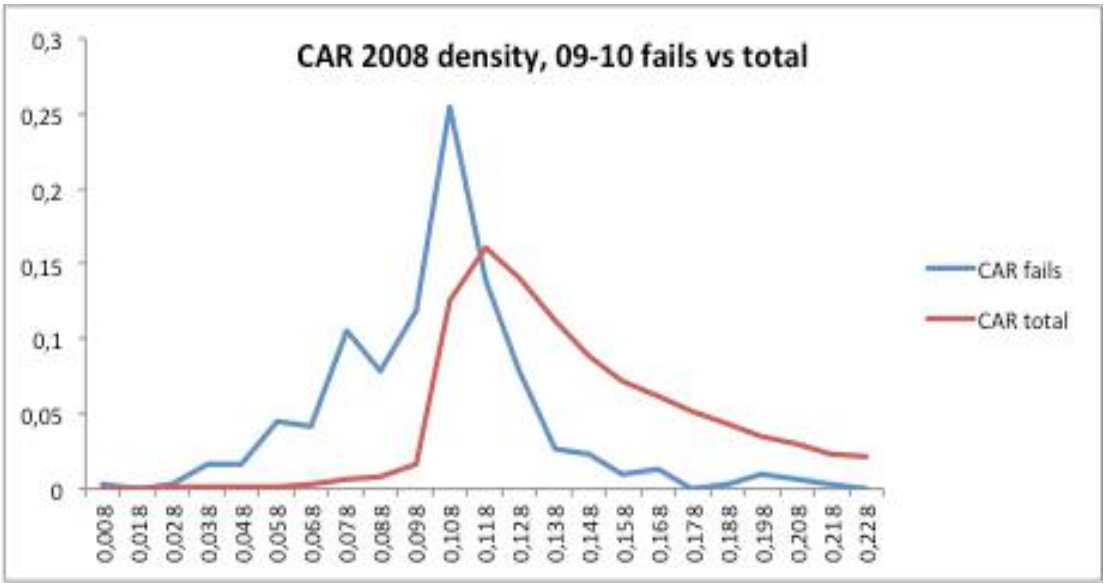


Figure A17. The chart displays the 2008 CAR density split by the group of default banks in 2009-2010 to the total population of FDIC insured institutions. Densities are expressed as the share of observations (y-axis) occurring at each CAR magnitude (x-axis).

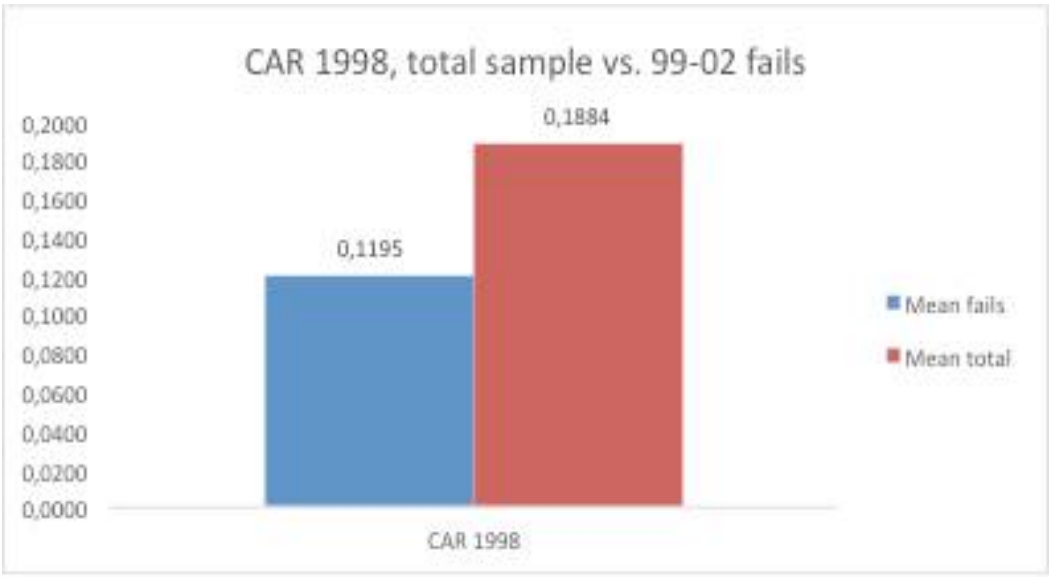


Figure A18. The chart displays the 1998 CAR (regulatory capital to risk-weighted assets), derived from the balance sheets of all FDIC certified banks that existed in 1998. The presentation is split on the subgroup of banks that defaulted between 1999 and 2002 and the population of FDIC insured institutions.

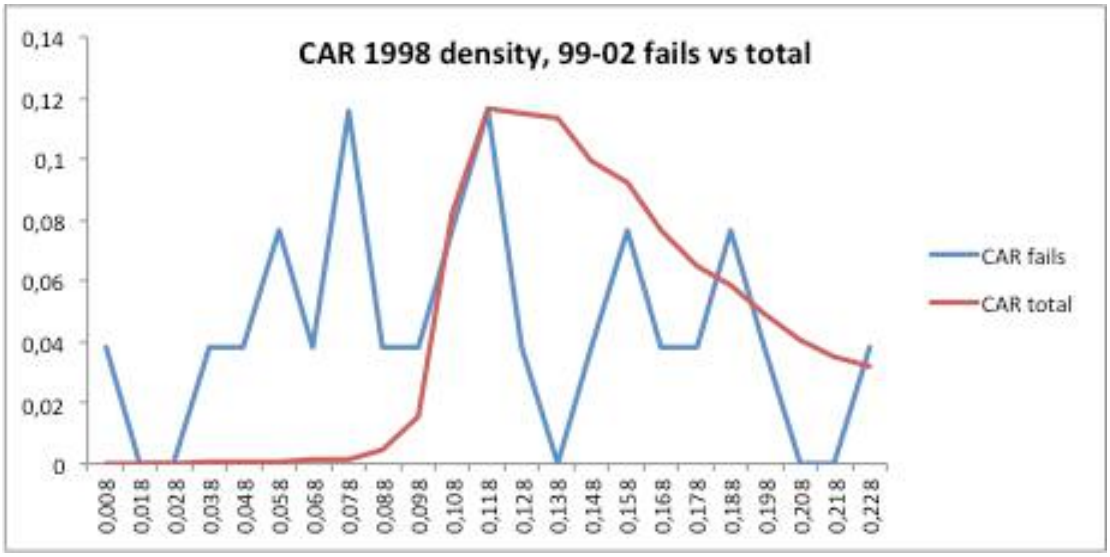


Figure A19. The chart displays the 1998 CAR density split by the group of default banks in 1999-2002 to the total population of FDIC insured institutions. Densities are expressed as the share of observations (y-axis) occurring at each CAR magnitude (x-axis).

Deposit interest rate measure

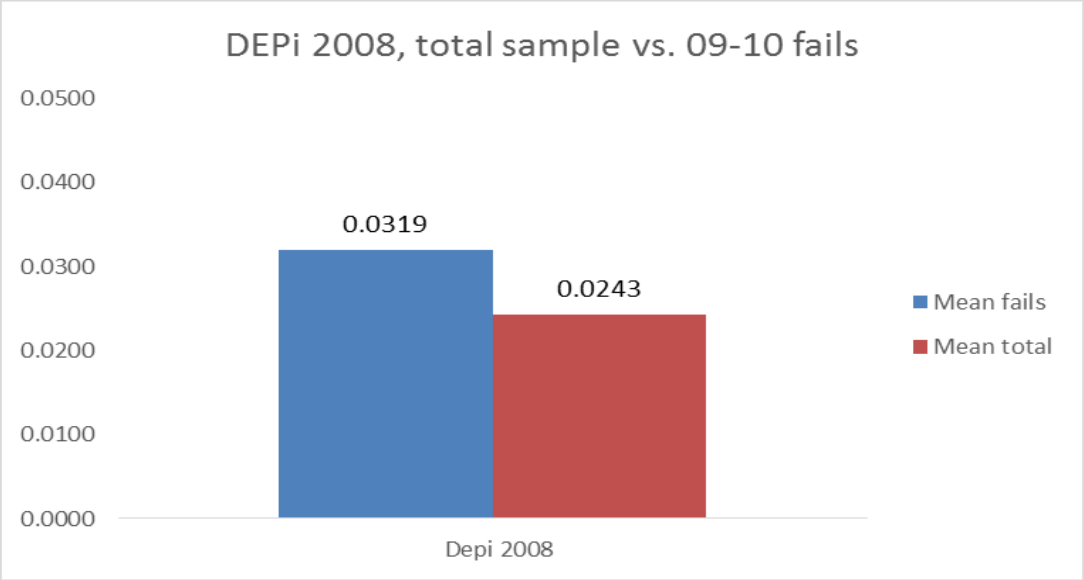


Figure A20. The chart displays the 2008 DEPi (average interest rate paid on deposits held) derived from the balance sheets and P&Ls of all FDIC certified banks that existed in 2008. The presentation is split on the subgroup of banks that defaulted between 2009 and 2010 and the population of FDIC insured institutions.

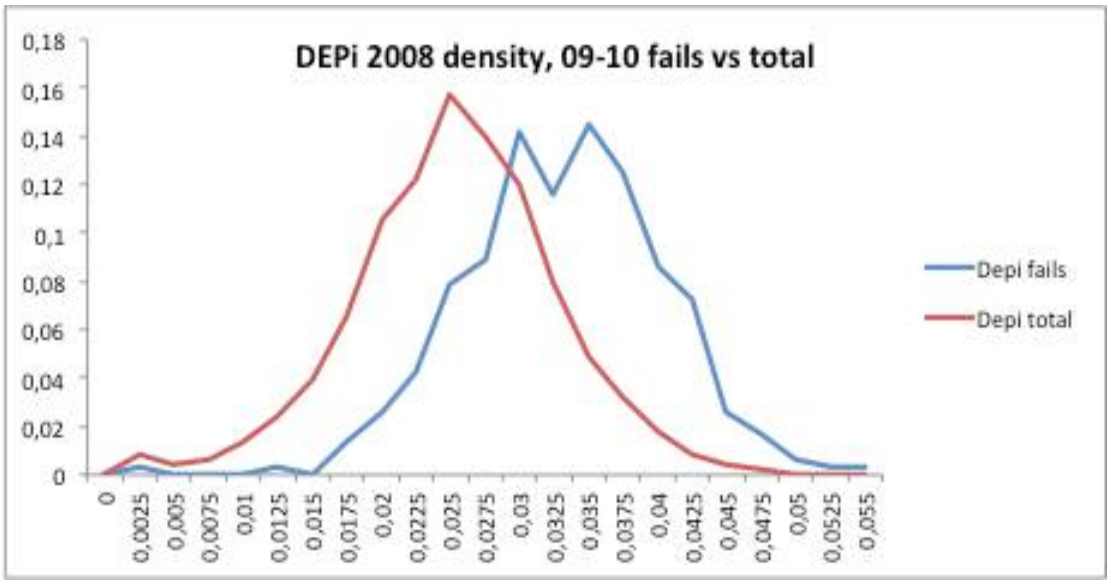


Figure A21. The chart displays the 2008 DEPi density split by the group of default banks in 2009-2010 to the total population of FDIC insured institutions. Densities are expressed as the share of observations (y-axis) occurring at each DEPi magnitude (x-axis).

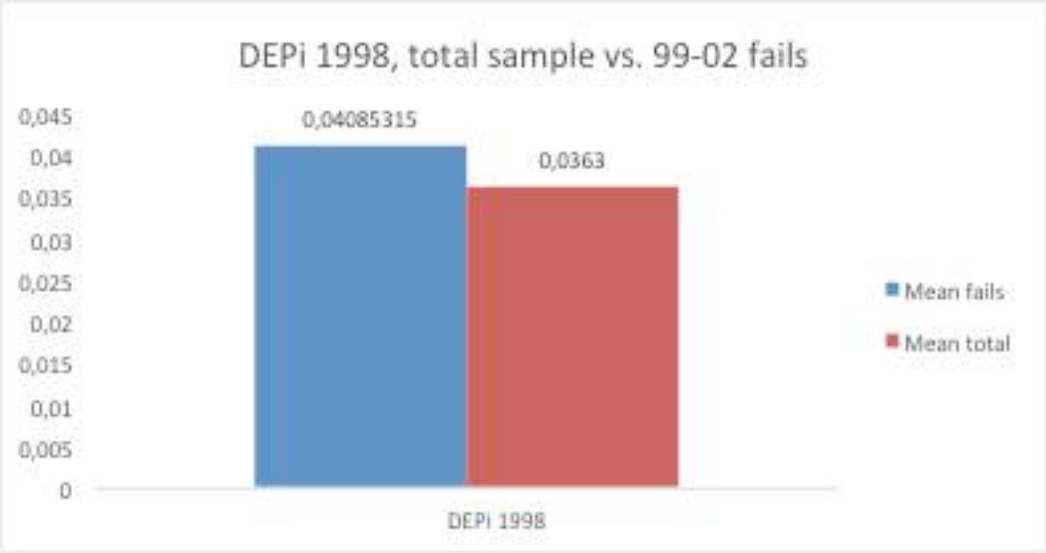


Figure A22. The chart displays the 1998 DEPi (average interest rate paid on deposits held) derived from the balance sheets and P&Ls of all FDIC certified banks that existed in 1998. The presentation is split on the subgroup of banks that defaulted between 1999 and 2002 and the population of FDIC insured institutions.

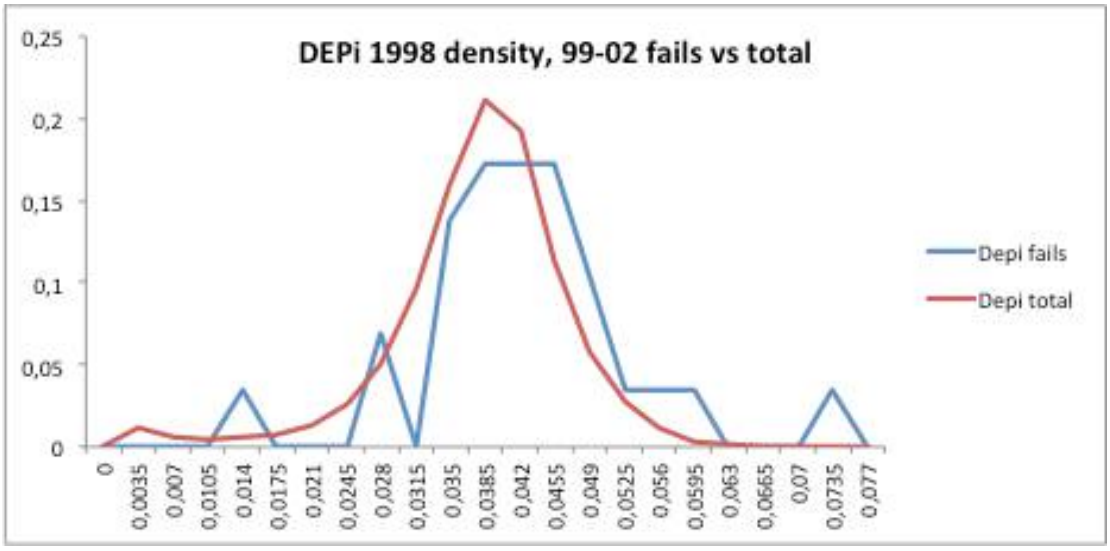


Figure A23. The chart displays the 1998 DEPi density split by the group of default banks in 1999-2002 to the total population of FDIC insured institutions. Densities are expressed as the share of observations (y-axis) occurring at each DEPi magnitude (x-axis).

Income diversification measure

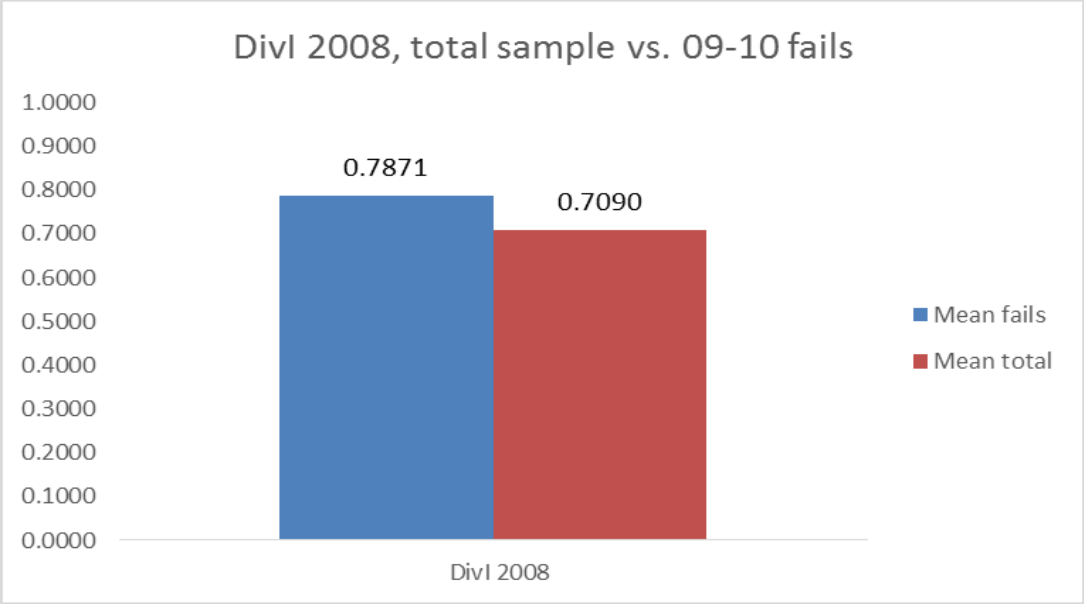


Figure A24. The chart displays the 2008 DivI (average Hirschmann-Herfindahl Index for income) derived from the P&Ls of all FDIC certified banks that existed in 2008. The presentation is split on the subgroup of banks that defaulted between 2009 and 2010 and the population of FDIC insured institutions.

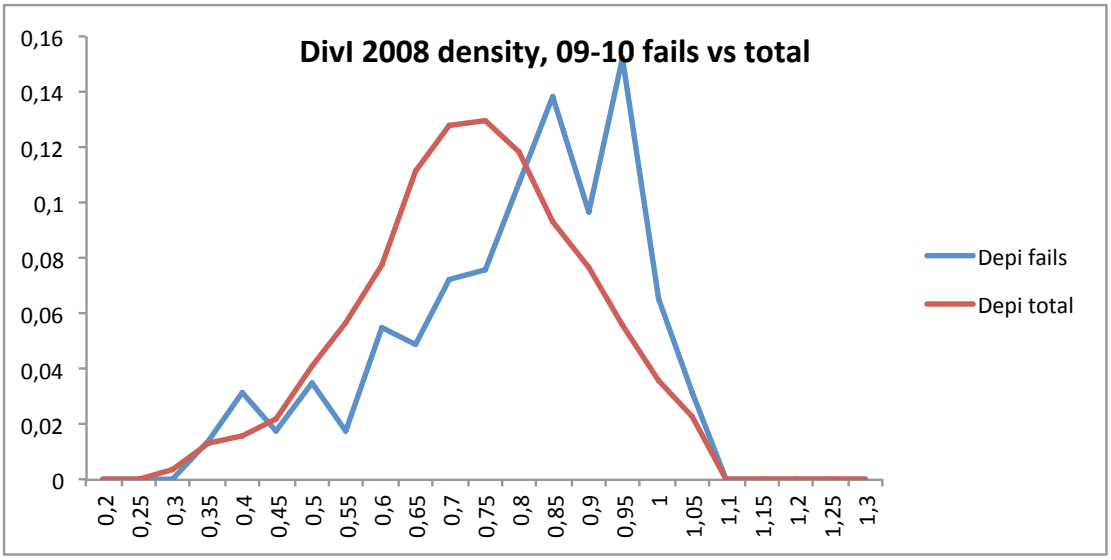


Figure A25. The chart displays the 2008 DivI density split by the group of default banks in 2009-2010 to the total population of FDIC insured institutions. Densities are expressed as the share of observations (y-axis) occurring at each DivI magnitude (x-axis).

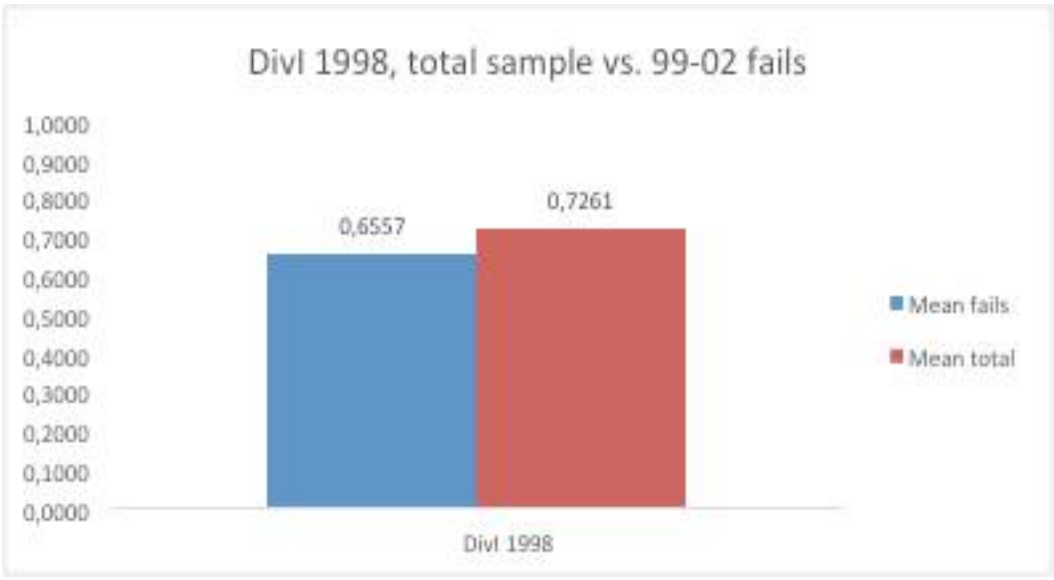


Figure A26. The chart displays the 1998 DivI (average Hirschmann-Herfindahl Index for income) derived from the P&Ls of all FDIC certified banks that existed in 1998. The presentation is split on the subgroup of banks that defaulted between 1999 and 2002 and the population of FDIC insured institutions.

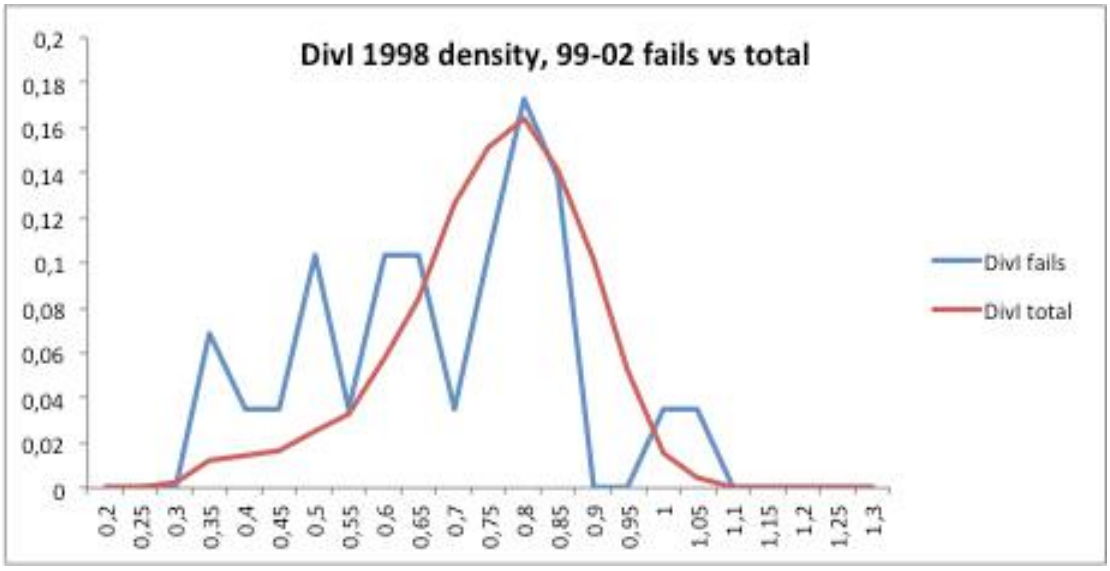


Figure A27. The chart displays the 1998 DivI density split by the group of default banks in 1999-2002 to the total population of FDIC insured institutions. Densities are expressed as the share of observations (y-axis) occurring at each DivI magnitude (x-axis).

Loan diversification measure

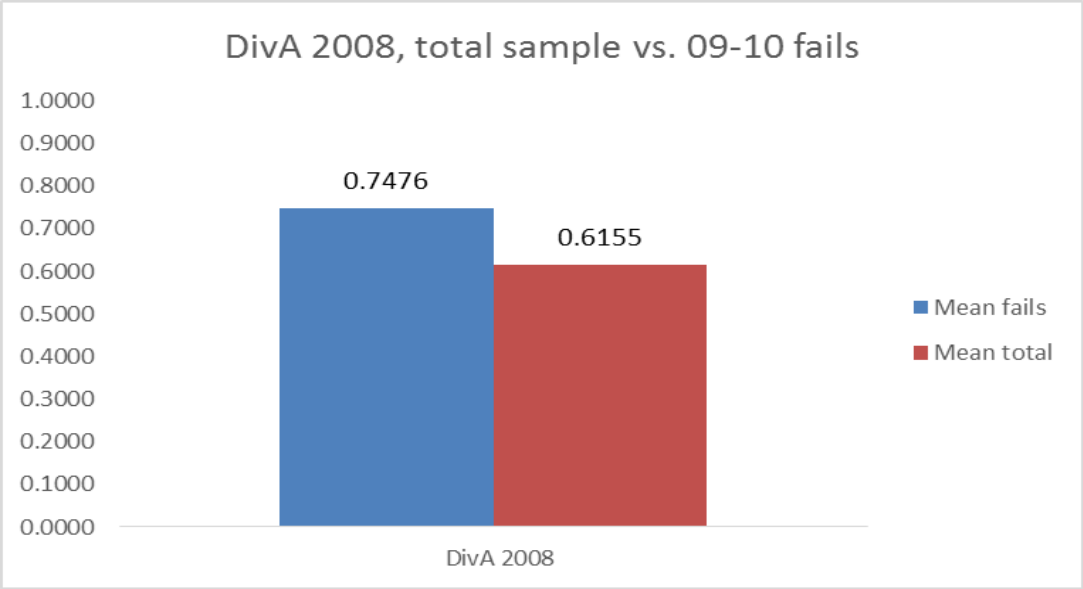


Figure A28. The chart displays the 2008 DivA (average Hirschmann-Herfindahl Index for loans) derived from the balance sheets of all FDIC certified banks that existed in 2008. The presentation is split on the subgroup of banks that defaulted between 2009 and 2010 and the population of FDIC insured institutions.

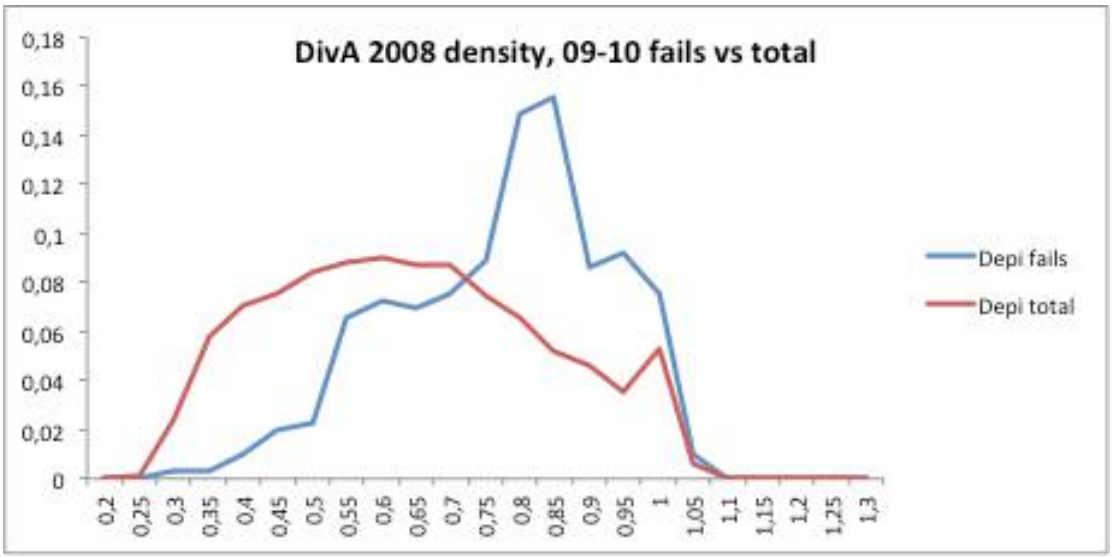


Figure A29. The chart displays the 2008 DivA density split by the group of default banks in 2009-2010 to the total population of FDIC insured institutions. Densities are expressed as the share of observations (y-axis) occurring at each DivA magnitude (x-axis).

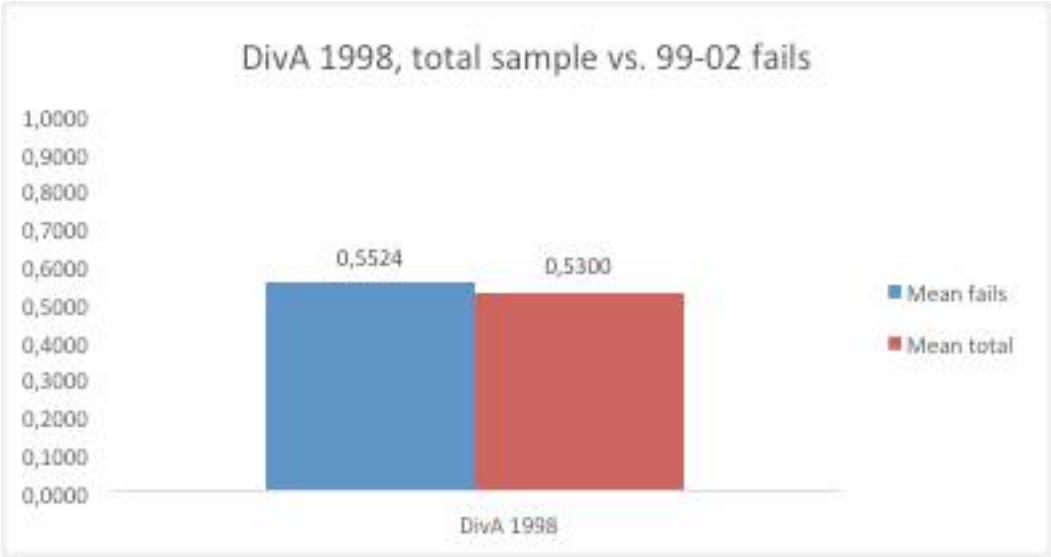


Figure A30. The chart displays the 1998 DivA (average Hirschmann-Herfindahl Index for loans) derived from the balance sheets of all FDIC certified banks that existed in 1998. The presentation is split on the subgroup of banks that defaulted between 1999 and 2002 and the population of FDIC insured institutions.

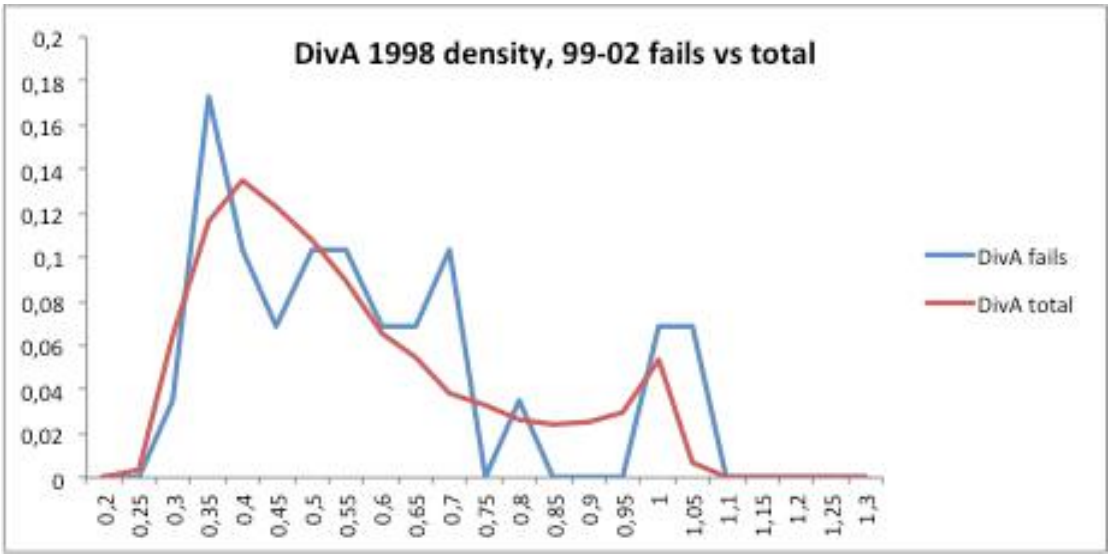


Figure A31. The chart displays the 1998 DivA density split by the group of default banks in 1999-2002 to the total population of FDIC insured institutions. Densities are expressed as the share of observations (y-axis) occurring at each DivA magnitude (x-axis).

Loan growth measure

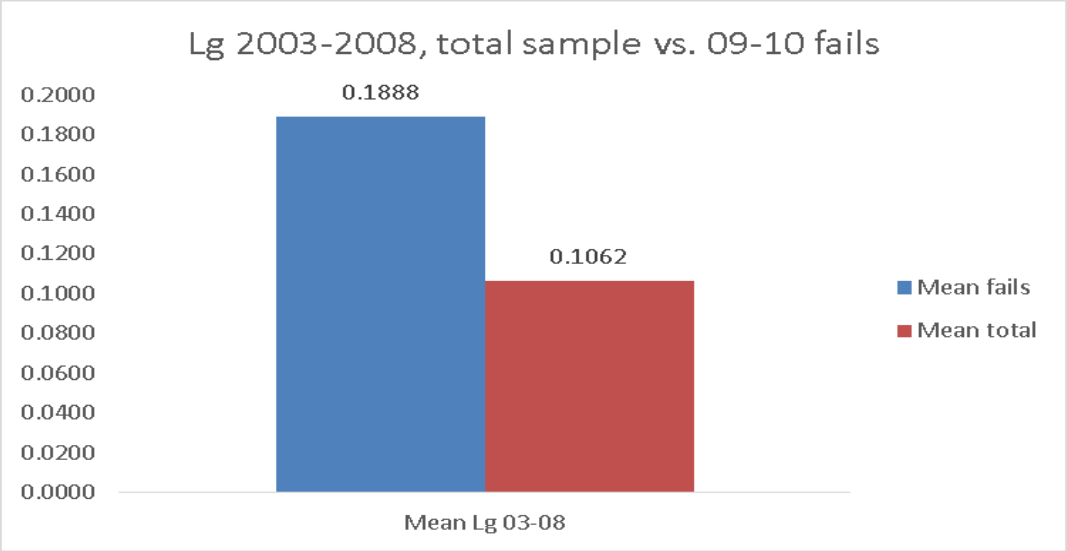


Figure A32. The chart displays the 2003-2008 Lg (geometric average growth rate for combined loans) derived from the balance sheets of all FDIC certified banks that existed over the full 2003-2008 period. The presentation is split on the subgroup of banks that defaulted between 2009 and 2010 and the population of FDIC insured institutions.

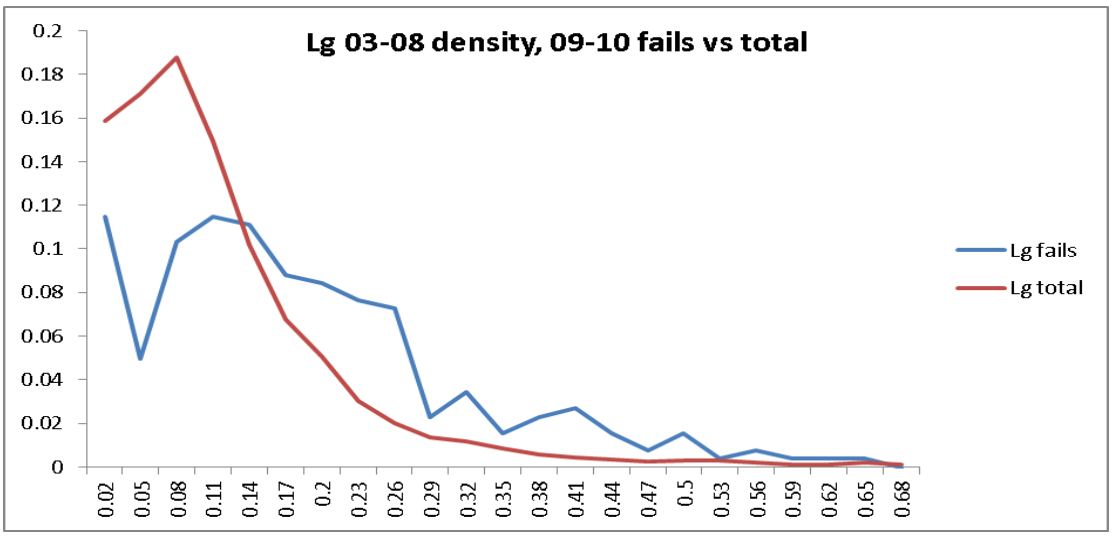


Figure A33. The chart displays the 2003-2008 Lg density split by the group of default banks in 2009-2010 to the total population of FDIC insured institutions. Densities are expressed as the share of observations (y-axis) occurring at each Lg magnitude (x-axis).

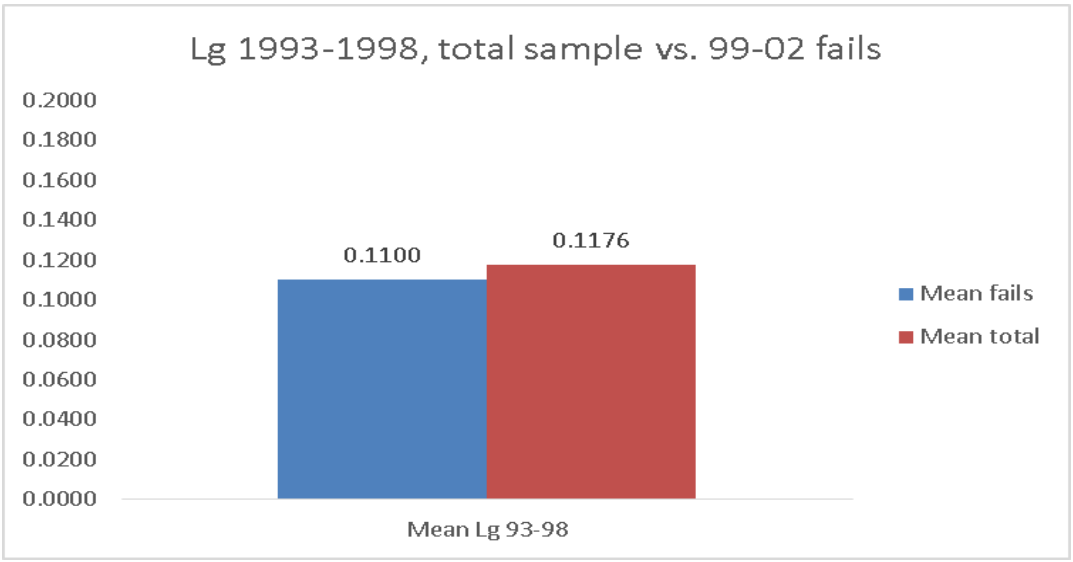


Figure A34. The chart displays the 1993-1998 Lg (geometric average growth rate for combined loans) derived from the balance sheets of all FDIC certified banks that existed over the full 1993-1998 period. The presentation is split on the subgroup of banks that defaulted between 1999 and 2002 and the population of FDIC insured institutions.

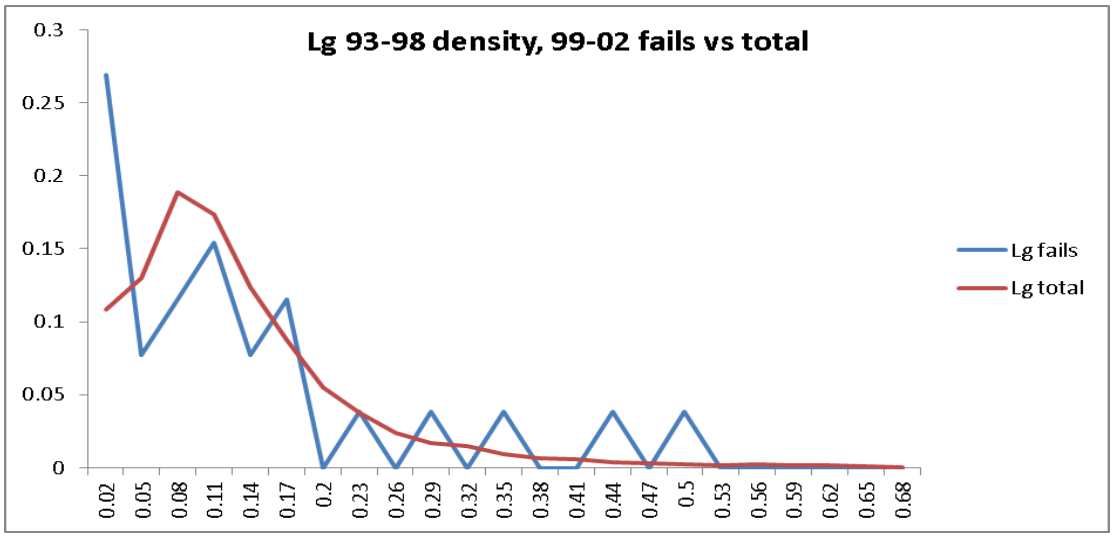


Figure A35. The chart displays the 1993-1998 Lg density split by the group of default banks in 1999-2002 to the total population of FDIC insured institutions. Densities are expressed as the share of observations (y-axis) occurring at each Lg magnitude (x-axis).

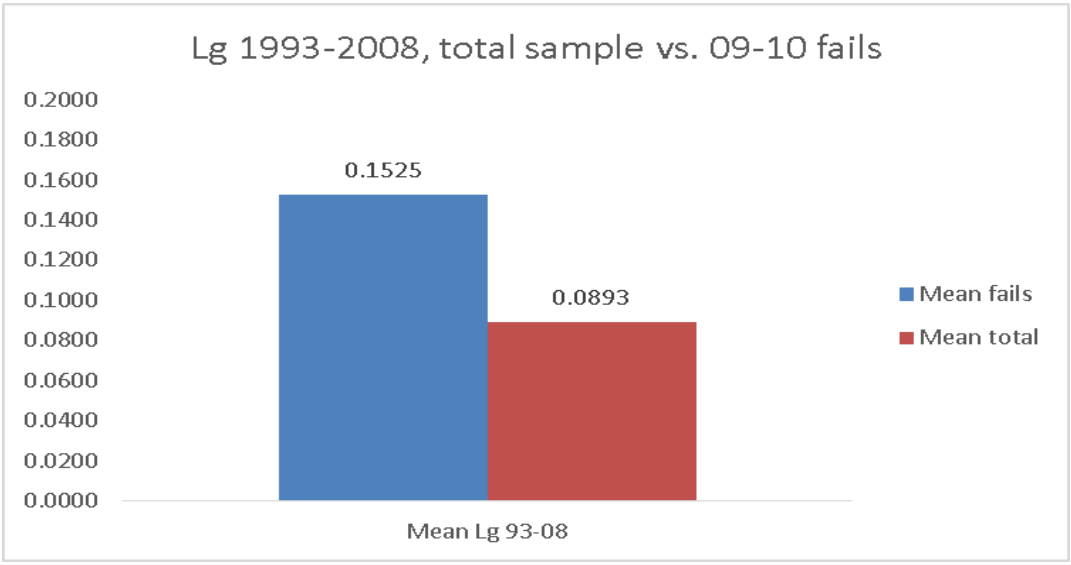


Figure A36. The chart displays the 1993-2008 Lg (geometric average growth rate for combined loans) derived from the balance sheets of all FDIC certified banks that existed over the full 1993-2008 period. The presentation is split on the subgroup of banks that defaulted between 2009 and 2010 and the population of FDIC insured institutions.

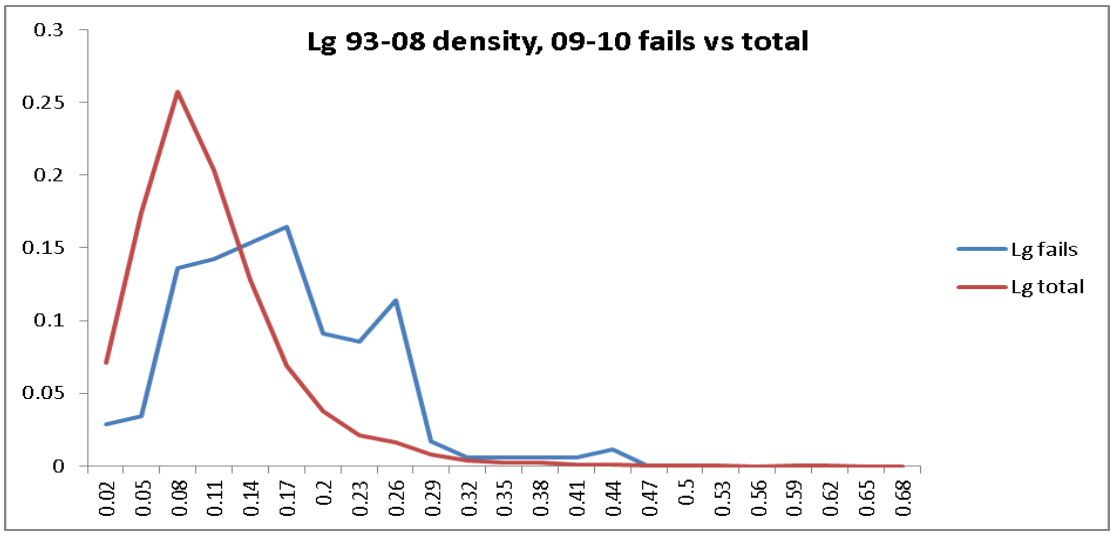


Figure A37. The chart displays the 1993-2008 Lg density split by the group of default banks in 2009-2010 to the total population of FDIC insured institutions. Densities are expressed as the share of observations (y-axis) occurring at each Lg magnitude (x-axis).

Inferential Testing Appendix

STATA model tests[46]

Multicollinearity - If two explanatory variables are highly correlated with each other, they can cause problems during analysis because they are explaining almost the same variability in the outcome. Therefore, it is beneficial to examine associations between explanatory variables and exclude one variable in a pair of highly correlated variables before proceeding with testing. In STATA, the command *collin* is used to obtain variance inflation factors. To confidently exclude multicollinearity, we would like to see VIFs of below 10 for each variable.

Specification - The link test is a test to assess model specification. Ideally we would want to see an insignificant hat square, which is a sign that that there is no specification error such as omitted variables that significantly explain the dependent variable or that there might be some issue with how the dependent variable is specified. If relevant variables are omitted from the model, the common variance they share with included variables may be wrongly attributed to those variables and the error term is inflated. The link test is based on the idea that if a regression is specified correctly, it should not be possible to find additional independent variables that are significant except by chance. The STATA function *linktest* creates two new variables, the variable of prediction, *_hat*, and the variable of squared prediction, *_hatsq*. The model is then refit using these two variables as predictors. _hat should be significant since it is the predicted value but *_hatsq* should not, because if the model is specified correctly, the squared predictions should not have much explanatory power.

Goodness-of-fit - Testing goodness-of-fit is used to verify whether the model fits the data or whether there is any under- or over- residual dispersion. We use the Hosmer-Lemeshow goodness-of-fit test, which can be used for binomial outcome models.

Influential cases - are of importance and interest for several reasons. They might be data entry errors, they may be of interest by themselves for us to study and they may badly skew the regression estimation. In order to identify influential cases, we plot residuals against predicted probabilities by first saving the standardized

[46] Section builds on:
Regressions (Ref # 1), Regressions (Ref # 2), Regressions (Ref # 3), Regressions (Ref # 4)

Pearson residuals and deviance residuals and then plot them against the bank cert numbers.

Linearity - We test the assumption of linearity by producing a Lowes graph. When we build a logistic regression model, we assume that the logistic of the outcome variable is a linear combination of the independent variables and so we want to check whether or not this assumption holds.

Summary statistics tables of the variables

					Quantiles			
Variable	n	Mean	S.D.	Min	.25	Mdn	.75	Max
br2008	business risk CoV							
br2008	5094	0.54	0.10	0.29	0.48	0.51	0.57	1.56
car2008	capital adequacy ratio							
car2008	5094	0.16	0.10	0.02	0.12	0.14	0.18	3.82
dep2008	avg interest rate on deposits							
dep2008	5094	0.02	0.01	0.00	0.02	0.02	0.03	0.08
divi2008	income diversification							
divi2008	5094	0.67	0.13	0.27	0.59	0.68	0.77	1.00
diva2008	asset(loan) diversification							
diva2008	5094	0.56	0.17	0.21	0.42	0.55	0.68	1.00
lg2008	geometic mean loan growth '03-'08							
lg2008	5094	0.09	0.10	-0.71	0.04	0.07	0.12	1.96
size2008	deposit size in '000 USD							
size2008	5094	1.0e+06	1.6e+07	500.00	55741.00	1.2e+05	2.7e+05	7.5e+08

					Quantiles			
Variable	n	Mean	S.D.	Min	.25	Mdn	.75	Max
br1998	business risk CoV							
br1998	9644	0.54	0.11	0.28	0.47	0.51	0.57	1.91
car1998	capital adequacy ratio							
car1998	9644	0.19	0.16	-0.04	0.13	0.16	0.21	8.04
dep1998	avg interest rate on deposits							
dep1998	9644	0.04	0.01	0.00	0.03	0.04	0.04	0.24
divi1998	income diversification							
divi1998	9644	0.73	0.13	0.27	0.65	0.74	0.82	1.00
diva1998	asset(loan) diversification							
diva1998	9644	0.53	0.20	0.21	0.37	0.47	0.64	1.00
lg1998	geometic mean loan growth '93-'98							
lg1998	9644	0.12	0.15	-0.88	0.05	0.09	0.15	4.06
size1998	deposit size in '000 USD							
size1998	9644	3.8e+05	4.1e+06	0.00	30682.25	62156.29	1.3e+05	1.8e+08

Univariable logistic regressions

1998 data:

Logistic regression — Number of obs = 9644; LR chi2(1) = 15.57; Prob > chi2 = 0.0001; Log likelihood = -160.08784; Pseudo R2 = 0.0464

fails9902	Odds Ratio	Std. Err.	z	P>|z|	[95% Conf.	Interval]
br1998	54.38642	41.63512	5.22	0.000	12.12996	243.8493

Logistic regression — Number of obs = 9644; LR chi2(1) = 40.33; Prob > chi2 = 0.0000; Log likelihood = -147.7114; Pseudo R2 = 0.1201

fails9902	Odds Ratio	Std. Err.	z	P>|z|	[95% Conf.	Interval]
car1998	4.69e-17	3.30e-16	-5.34	0.000	4.83e-23	4.56e-11

Note: 242 failures and 0 successes completely determined.

Logistic regression — Number of obs = 9644; LR chi2(1) = 0.88; Prob > chi2 = 0.3476; Log likelihood = -167.4339; Pseudo R2 = 0.0026

fails9902	Odds Ratio	Std. Err.	z	P>|z|	[95% Conf.	Interval]
dep1998	4.28e+07	6.24e+08	1.21	0.228	.000017	1.08e+20

Logistic regression — Number of obs = 9644; LR chi2(1) = 7.40; Prob > chi2 = 0.0065; Log likelihood = -164.17295; Pseudo R2 = 0.0221

fails9902	Odds Ratio	Std. Err.	z	P>|z|	[95% Conf.	Interval]
divi1998	.0220785	.0294854	-2.86	0.004	.0016114	.3025036

Logistic regression — Number of obs = 9644; LR chi2(1) = 0.00; Prob > chi2 = 0.9925; Log likelihood = -167.87497; Pseudo R2 = 0.0000

fails9902	Odds Ratio	Std. Err.	z	P>|z|	[95% Conf.	Interval]
diva1998	1.009546	1.017884	0.01	0.992	.1399248	7.283799

Logistic regression — Number of obs = 9644; LR chi2(1) = 0.00; Prob > chi2 = 0.9774; Log likelihood = -167.87461; Pseudo R2 = 0.0000

fails9902	Odds Ratio	Std. Err.	z	P>|z|	[95% Conf.	Interval]
lg1998	.9625408	1.30813	-0.03	0.978	.0670816	13.81131

Logistic regression — Number of obs = 9644; LR chi2(1) = 0.24; Prob > chi2 = 0.6215; Log likelihood = -167.75315; Pseudo R2 = 0.0007

fails9902	Odds Ratio	Std. Err.	z	P>|z|	[95% Conf.	Interval]
size1998	.9999999	3.21e-07	-0.34	0.737	.9999993	1.000001

Note: 4 failures and 0 successes completely determined.

2008 data:

Logistic regression — Number of obs = 5094; LR chi2(1) = 35.45; Prob > chi2 = 0.0000; Log likelihood = -531.92039; Pseudo R2 = 0.0322

fails0910	Odds Ratio	Std. Err.	z	P>|z|	[95% Conf.	Interval]
br2008	56.19377	33.13315	6.83	0.000	17.69294	178.4746

Logistic regression — Number of obs = 5094; LR chi2(1) = 298.46; Prob > chi2 = 0.0000; Log likelihood = -400.41438; Pseudo R2 = 0.2715

fails0910	Odds Ratio	Std. Err.	z	P>|z|	[95% Conf.	Interval]
car2008	1.30e-33	7.70e-33	-12.81	0.000	1.22e-38	1.40e-28

Note: 168 failures and 0 successes completely determined.

Logistic regression — Number of obs = 5094; LR chi2(1) = 116.13; Prob > chi2 = 0.0000; Log likelihood = -491.58114; Pseudo R2 = 0.1056

fails0910	Odds Ratio	Std. Err.	z	P>|z|	[95% Conf.	Interval]
dep2008	2.70e+63	3.92e+64	10.04	0.000	1.11e+51	6.55e+75

Logistic regression — Number of obs = 5094; LR chi2(1) = 18.70; Prob > chi2 = 0.0000; Log likelihood = -540.29291; Pseudo R2 = 0.0170

fails0910	Odds Ratio	Std. Err.	z	P>|z|	[95% Conf.	Interval]
divi2008	24.86366	18.84055	4.24	0.000	5.630715	109.791

Logistic regression — Number of obs = 5094; LR chi2(1) = 72.54; Prob > chi2 = 0.0000; Log likelihood = -513.37492; Pseudo R2 = 0.0660

fails0910	Odds Ratio	Std. Err.	z	P>|z|	[95% Conf.	Interval]
diva2008	100.0835	55.54636	8.30	0.000	33.72452	297.0158

Logistic regression — Number of obs = 5094; LR chi2(1) = 19.15; Prob > chi2 = 0.0000; Log likelihood = -540.06951; Pseudo R2 = 0.0174

fails0910	Odds Ratio	Std. Err.	z	P>|z|	[95% Conf.	Interval]
lg2008	13.1405	6.886482	4.91	0.000	4.70464	36.70263

Logistic regression — Number of obs = 5094; LR chi2(1) = 0.04; Prob > chi2 = 0.8451; Log likelihood = -549.62489; Pseudo R2 = 0.0000

fails0910	Odds Ratio	Std. Err.	z	P>|z|	[95% Conf.	Interval]
size2008	1	4.43e-09	0.21	0.831	1	1

Multivariable logistic regressions

Logistic regression — Number of obs = 9644; LR chi2(7) = 57.65; Prob > chi2 = 0.0000; Log likelihood = -139.05184; Pseudo R2 = 0.1717

fails9902	Odds Ratio	Std. Err.	z	P>|z|	[95% Conf.	Interval]
br1998	48.98197	61.62135	3.09	0.002	4.16092	576.6112
car1998	3.72e-15	2.59e-14	-4.78	0.000	4.55e-21	3.05e-09
dep1998	2.77e+13	6.47e+14	1.33	0.185	3.66e-07	2.10e+33
divi1998	.2643568	.412394	-0.85	0.394	.0124258	5.624145
diva1998	.6716471	.789764	-0.34	0.735	.0670264	6.730331
lg1998	.1017395	.1467948	-1.58	0.113	.0060164	1.720465
size1998	.9999997	5.05e-07	-0.66	0.507	.9999987	1.000001

Note: 197 failures and 0 successes completely determined.

Logistic regression — Number of obs = 5094; LR chi2(7) = 403.14; Prob > chi2 = 0.0000; Log likelihood = -348.07463; Pseudo R2 = 0.3667

fails0910	Odds Ratio	Std. Err.	z	P>|z|	[95% Conf.	Interval]
br2008	8.417618	6.841266	2.62	0.009	1.711554	41.3988
car2008	8.53e-28	5.07e-27	-10.49	0.000	7.46e-33	9.75e-23
dep2008	6.39e+54	1.26e+56	6.39	0.000	1.01e+38	4.06e+71
divi2008	.3119837	.2581038	-1.41	0.159	.0616501	1.578811
diva2008	41.10172	28.11986	5.43	0.000	10.75246	157.113
lg2008	.4646335	.4310178	-0.83	0.409	.075421	2.862388
size2008	1	4.67e-09	0.81	0.421	1	1

Note: 135 failures and 0 successes completely determined.

Multivariable reduced models

Logistic regression — Number of obs = 9644; LR chi2(2) = 47.18; Prob > chi2 = 0.0000; Log likelihood = -144.28378; Pseudo R2 = 0.1405

fails9902	Odds Ratio	Std. Err.	z	P>|z|	[95% Conf.	Interval]
br1998	22.09852	21.07849	3.25	0.001	3.407624	143.3094
car1998	8.25e-15	5.92e-14	-4.51	0.000	6.34e-21	1.07e-08

Note: 173 failures and 0 successes completely determined.

```
. logistic fails0910 br2008 car2008 dep2008 diva2008
```

Logistic regression — Number of obs = 5094; LR chi2(4) = 400.09; Prob > chi2 = 0.0000; Log likelihood = -349.59728; Pseudo R2 = 0.3640

fails0910	Odds Ratio	Std. Err.	z	P>|z|	[95% Conf.	Interval]
br2008	6.34506	5.010557	2.34	0.019	1.349772	29.82712
car2008	3.04e-27	1.78e-26	-10.41	0.000	3.11e-32	2.97e-22
dep2008	2.01e+49	3.65e+50	6.25	0.000	7.06e+33	5.73e+64
diva2008	35.46347	23.72822	5.33	0.000	9.555458	131.6167

Note: 129 failures and 0 successes completely determined.

Collinearity testing

Collinearity Diagnostics

Variable	VIF	SQRT VIF	Tolerance	R-Squared
fails9902	1.01	1.00	0.9948	0.0052
br1998	1.21	1.10	0.8295	0.1705
car1998	1.10	1.05	0.9117	0.0883
dep1998	1.26	1.12	0.7940	0.2060
divi1998	1.30	1.14	0.7688	0.2312
diva1998	1.15	1.07	0.8710	0.1290
lg1998	1.20	1.10	0.8330	0.1670
size1998	1.04	1.02	0.9584	0.0416
Mean VIF	1.16			

	Eigenval	Cond Index
1	5.8627	1.0000
2	1.0380	2.3766
3	0.9978	2.4240
4	0.6327	3.0439
5	0.2993	4.4258
6	0.0931	7.9356
7	0.0447	11.4490
8	0.0227	16.0534
9	0.0090	25.5587
Condition Number		25.5587

Eigenvalues & Cond Index computed from scaled raw sscp (w/ intercept)
Det(correlation matrix) 0.5541

Collinearity Diagnostics

Variable	VIF	SQRT VIF	Tolerance	R-Squared
fails0910	1.06	1.03	0.9474	0.0526
br2008	1.05	1.03	0.9479	0.0521
car2008	1.11	1.05	0.9028	0.0972
dep2008	1.22	1.11	0.8169	0.1831
divi2008	1.18	1.09	0.8462	0.1538
diva2008	1.05	1.02	0.9554	0.0446
lg2008	1.14	1.07	0.8740	0.1260
size2008	1.01	1.01	0.9883	0.0117
Mean VIF	1.10			

	Eigenval	Cond Index
1	6.0895	1.0000
2	1.0003	2.4673
3	0.9794	2.4935
4	0.5761	3.2511
5	0.1986	5.5379
6	0.0722	9.1847
7	0.0451	11.6211
8	0.0283	14.6648
9	0.0105	24.0659
Condition Number		24.0659

Eigenvalues & Cond Index computed from scaled raw sscp (w/ intercept)
Det(correlation matrix) 0.6727

From the collinearity testing we conclude that since both the individual and mean VIFs are considerably below 10[47], no significant collinearity exists between any of our parameters. The implication of this on the ability of the CAR variable to perfectly determine a great number of the dependent variable outcomes is that this is judged to be a good ability since there is no joint explanatory power between the CAR and any of the other parameters. We note that the test implies that the CAR is good at predicting bank default risk.

Correlations between the independent variables

	fai~9902	br1998	car1998	dep1998	divi1998	diva1998	lg1998	size1998
fails9902	1.0000							
br1998	0.0579	1.0000						
car1998	-0.0238	-0.0504	1.0000					
dep1998	0.0109	-0.0584	-0.0136	1.0000				
divi1998	-0.0295	-0.2025	0.1455	0.4028	1.0000			
diva1998	0.0001	0.1591	0.1373	0.2527	0.1806	1.0000		
lg1998	-0.0003	0.3146	-0.2244	-0.0620	-0.1271	-0.0387	1.0000	
size1998	-0.0026	0.0745	-0.0335	-0.0636	-0.1293	-0.0261	0.1715	1.0000

	fai~0910	br2008	car2008	dep2008	divi2008	diva2008	lg2008	size2008
fails0910	1.0000							
br2008	0.1034	1.0000						
car2008	-0.0910	-0.0201	1.0000					
dep2008	0.1683	0.0667	-0.0419	1.0000				
divi2008	0.0595	0.0071	0.0425	0.3803	1.0000			
diva2008	0.1218	0.1062	0.0005	0.1469	0.0426	1.0000		
lg2008	0.0800	0.1861	-0.2920	0.0556	0.0236	0.0886	1.0000	
size2008	0.0030	-0.0009	-0.0215	-0.0575	-0.0903	-0.0306	0.0411	1.0000

The correlation matrixes reveal no obvious cause for worry. The strongest positive correlation is found to be 0.40 and 0.38 for dep1998/divi1998 and dep2008/divi2008 respectively (DEPi/DivI) and the strongest negative correlation is -0.22 and -0.29 for car1998/lg1998 and car2008/lg2008 respectively (CAR/Lg). Interestingly these correlations hold across 10 years of time with very little change. Analyzing the first of these two pairwise correlations, we can conclude that there is some positive relationship between the average interest rate offered on deposits and diversification of income in the sense that they both tend to increase and decrease simultaneously. A possible reason for this relationship is that banks have concentrated their income sources have done so by lending aggressively, to less

[47] A VIF at 10 or above for a variable means that the variable could be considered as a linear combination of other independent variables in the model. This is something that should be avoided.

creditworthy counterparties. Such lending is usually conducted at higher interest rates (increased risk) so these banks have been able to offer higher deposit interest rates by taking higher risk in their income activities. This behavior is important for financial regulators to monitor since it may well be a breeding ground for other less suitable activities that collectively raise the probability of default. Turning to the other one, there is a negative relationship between the level of CAR and average loan portfolio growth. Specifically, as the CAR increases, loan growth decreases and vice versa. This makes sense, as the level of capital adequacy is directly dependent on the capital to assets relationship. If a bank pursues aggressive loan growth, ceteris paribus, the CAR should decrease as the asset base widens without necessarily increasing the amount of capital proportionately (since it is expensive for the bank to do so). Capital is largely guided by regulation (mind the phrase "regulatory capital") and is probably less adjustable to the actions or growth strategies employed by any specific bank.

Testing model specification – the link test

1998 full model:

```
. linktest

Iteration 0:   log likelihood = -167.87501
Iteration 1:   log likelihood = -166.72313
Iteration 2:   log likelihood = -162.74973  (backed up)
Iteration 3:   log likelihood = -158.13526
Iteration 4:   log likelihood = -154.97281
Iteration 5:   log likelihood = -154.41529  (backed up)
Iteration 6:   log likelihood = -153.90084  (backed up)
Iteration 7:   log likelihood = -141.12337
Iteration 8:   log likelihood = -138.79272
Iteration 9:   log likelihood = -138.78237
Iteration 10:  log likelihood = -138.78234
Iteration 11:  log likelihood = -138.78234

Logistic regression                               Number of obs   =       9644
                                                  LR chi2(2)      =      58.19
                                                  Prob > chi2     =     0.0000
Log likelihood = -138.78234                       Pseudo R2       =     0.1733

------------------------------------------------------------------------------
    fails9902 |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
--------------+---------------------------------------------------------------
        _hat |   1.036932   .1437426     7.21   0.000     .7552018    1.318663
      _hatsq |   .0037986   .0006984     5.44   0.000     .0024298    .0051674
       _cons |   .0809615   .7380885     0.11   0.913    -1.365665    1.527588
------------------------------------------------------------------------------
Note: 169 failures and 0 successes completely determined.
```

2008 full model:

```
. linktest

Iteration 0:   log likelihood = -549.64397
Iteration 1:   log likelihood = -449.73695
Iteration 2:   log likelihood = -448.16489  (backed up)
Iteration 3:   log likelihood = -428.26871
Iteration 4:   log likelihood = -420.55711
Iteration 5:   log likelihood = -417.06488
Iteration 6:   log likelihood = -416.22762  (backed up)
Iteration 7:   log likelihood = -415.54454  (backed up)
Iteration 8:   log likelihood = -350.03366
Iteration 9:   log likelihood =  -347.7599
Iteration 10:  log likelihood = -347.75437
Iteration 11:  log likelihood = -347.75407
Iteration 12:  log likelihood = -347.75407

Logistic regression                               Number of obs   =       5094
                                                  LR chi2(2)      =     403.78
                                                  Prob > chi2     =     0.0000
Log likelihood = -347.75407                       Pseudo R2       =     0.3673

------------------------------------------------------------------------------
    fails0910 |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
--------------+---------------------------------------------------------------
        _hat |   1.022197   .067263    15.20   0.000     .8903636    1.15403
      _hatsq |    .004291   .0005883    7.29   0.000     .0031381    .005444
       _cons |   .0170868   .1962419    0.09   0.931    -.3675403    .4017139
------------------------------------------------------------------------------
Note: 115 failures and 0 successes completely determined.
```

The significant *_hat* parameter indicates that the variables we have included are significant, which is desired of course. However, the *_hatsq* is also significant, meaning that we have either excluded potent variables from our regression model or that the link function is not correctly specified (i.e. the dependent variable does not properly relate to the independent variables). The case of the former, it is not strange in this case, as it would be difficult to claim that general bank default risk can be largely predicted by only six or seven variables. Rather, a comprehensive prediction would require us to investigate and perhaps include hundreds of variables. Bank default risk will depend on both systemic and idiosyncratic factors, furthering the complexity of such an omnipotent model. Here, we have to concede and realize that much more investigative work is needed on model specification if we want the model to become an excellent predictor of default

Testing goodness-of-fit

For goodness-of-fit, we perform Hosmer-Lemeshow tests with 5, 10, 15 and 20 quantiles.

```
. estat gof, group(5)

Logistic model for fails9902, goodness-of-fit test

  (Table collapsed on quantiles of estimated probabilities)

       number of observations =      9644
             number of groups =         5
     Hosmer-Lemeshow chi2(3) =        24.42
                 Prob > chi2 =         0.0000

. estat gof, group(10)

Logistic model for fails9902, goodness-of-fit test

  (Table collapsed on quantiles of estimated probabilities)

       number of observations =      9644
             number of groups =        10
     Hosmer-Lemeshow chi2(8) =        58.16
                 Prob > chi2 =         0.0000

. estat gof, group(15)

Logistic model for fails9902, goodness-of-fit test

  (Table collapsed on quantiles of estimated probabilities)

       number of observations =      9644
             number of groups =        15
    Hosmer-Lemeshow chi2(13) =        58.27
                 Prob > chi2 =         0.0000

. estat gof, group(20)

Logistic model for fails9902, goodness-of-fit test

  (Table collapsed on quantiles of estimated probabilities)

       number of observations =      9644
             number of groups =        20
    Hosmer-Lemeshow chi2(18) =        62.91
                 Prob > chi2 =         0.0000
```

```
. estat gof, group(5)

Logistic model for fails0910, goodness-of-fit test

  (Table collapsed on quantiles of estimated probabilities)

       number of observations =      5094
             number of groups =         5
     Hosmer-Lemeshow chi2(3) =        42.82
                 Prob > chi2 =         0.0000

. estat gof, group(10)

Logistic model for fails0910, goodness-of-fit test

  (Table collapsed on quantiles of estimated probabilities)

       number of observations =      5094
             number of groups =        10
     Hosmer-Lemeshow chi2(8) =      1472.19
                 Prob > chi2 =         0.0000

. estat gof, group(15)

Logistic model for fails0910, goodness-of-fit test

  (Table collapsed on quantiles of estimated probabilities)

       number of observations =      5094
             number of groups =        15
    Hosmer-Lemeshow chi2(13) =       356.35
                 Prob > chi2 =         0.0000

. estat gof, group(20)

Logistic model for fails0910, goodness-of-fit test

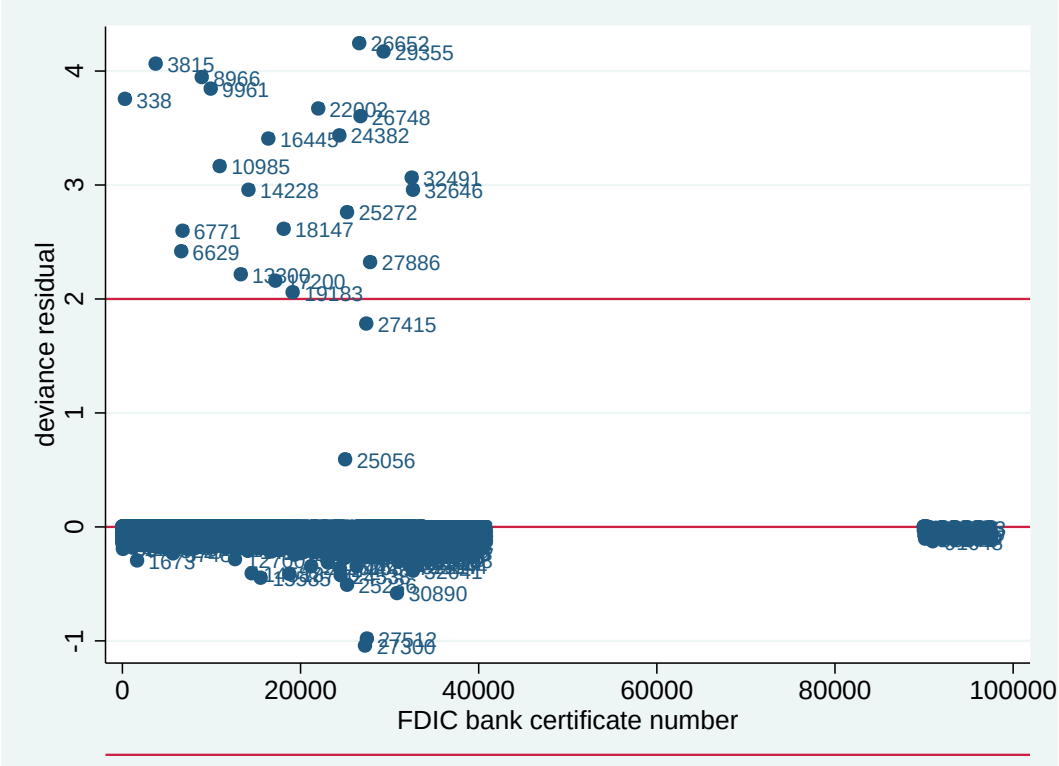
  (Table collapsed on quantiles of estimated probabilities)

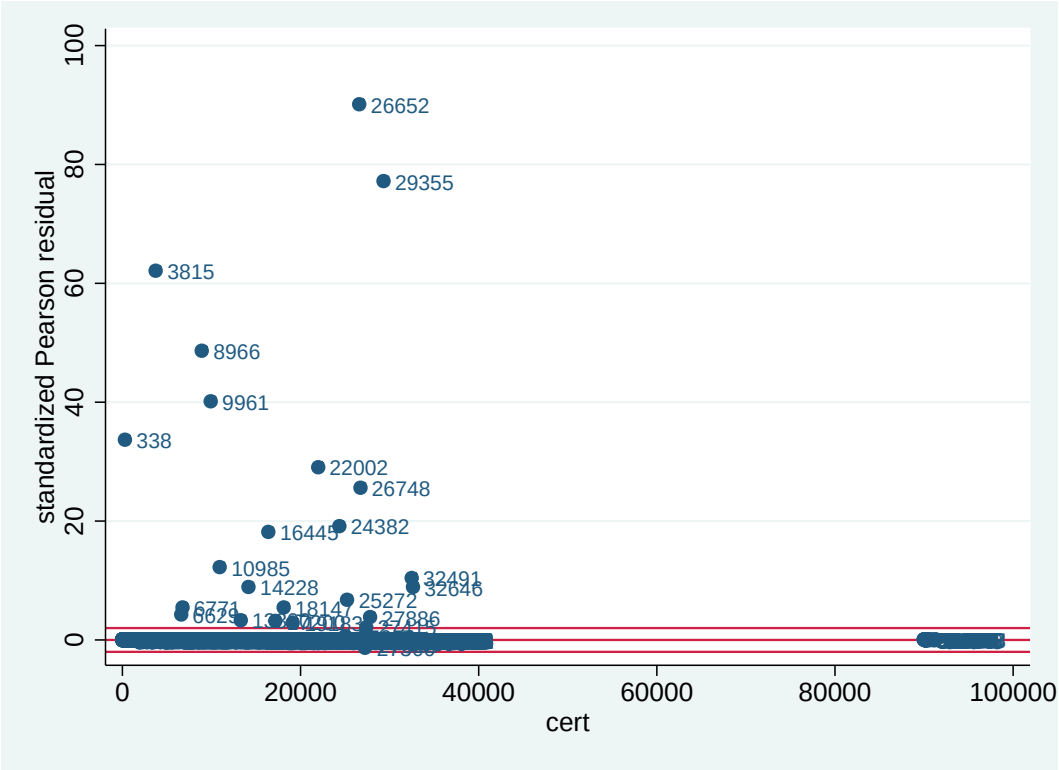
       number of observations =      5094
             number of groups =        20
    Hosmer-Lemeshow chi2(18) =      1516.38
                 Prob > chi2 =         0.0000
```

Analyzing the tests, we can reject our models as not fitting the data too well. This is not surprising considering the relatively narrow specification, as mentioned earlier.

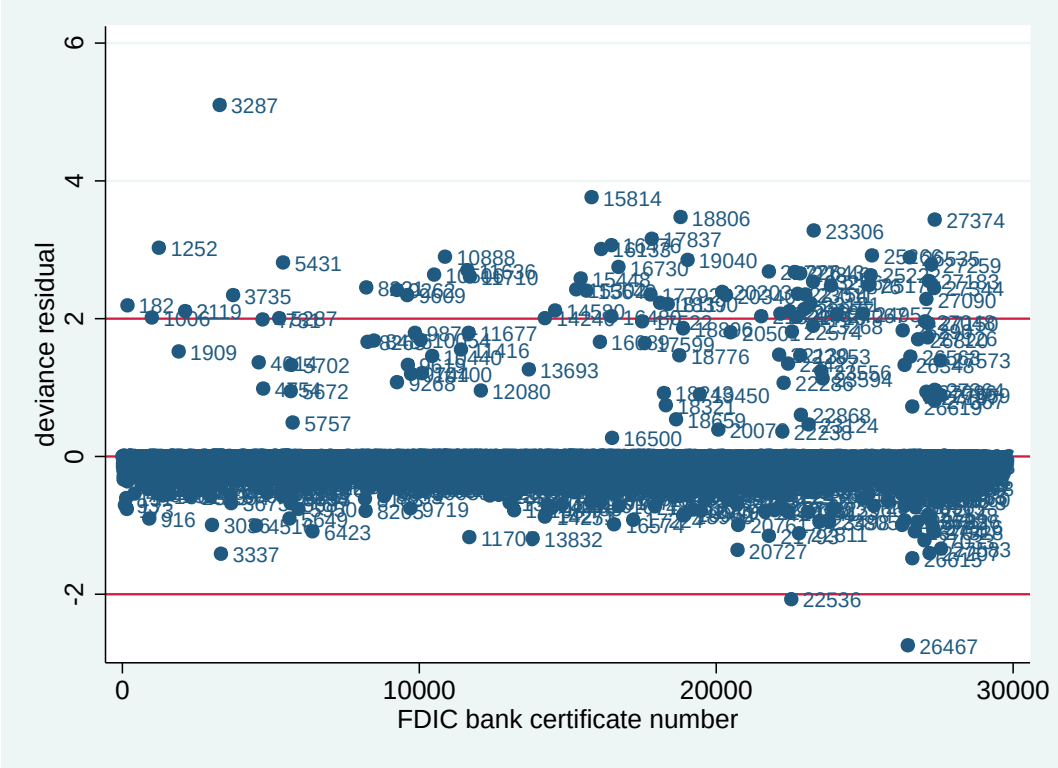
Testing for influential cases

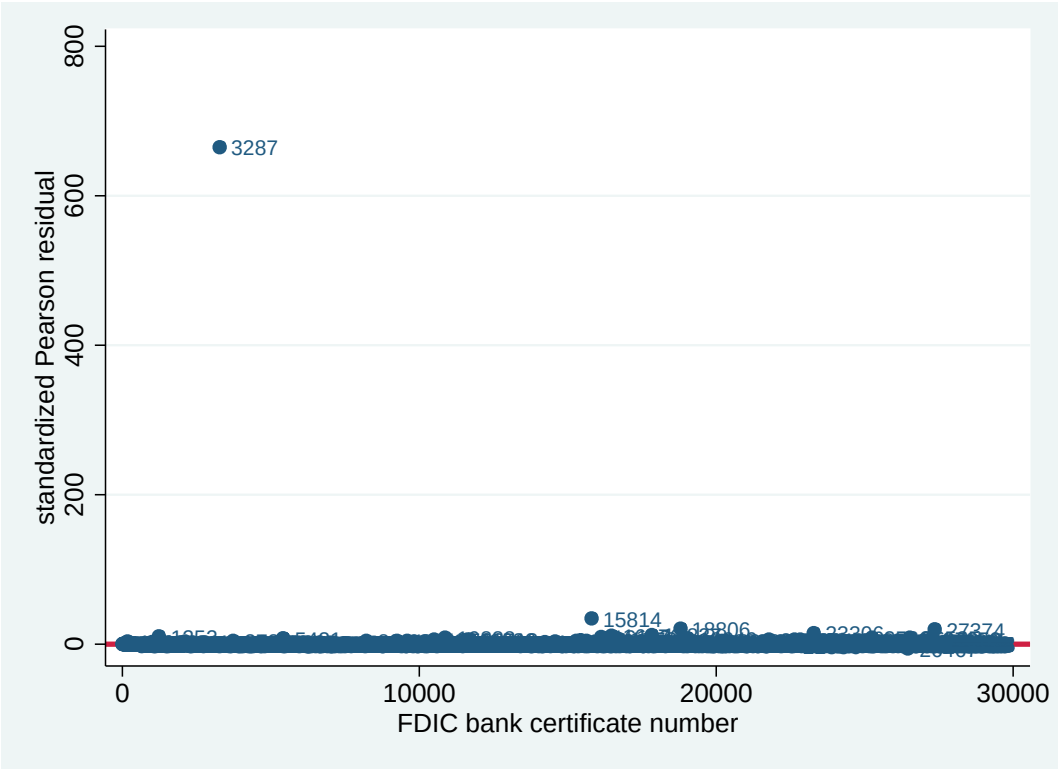
1998 data:





2008 data:



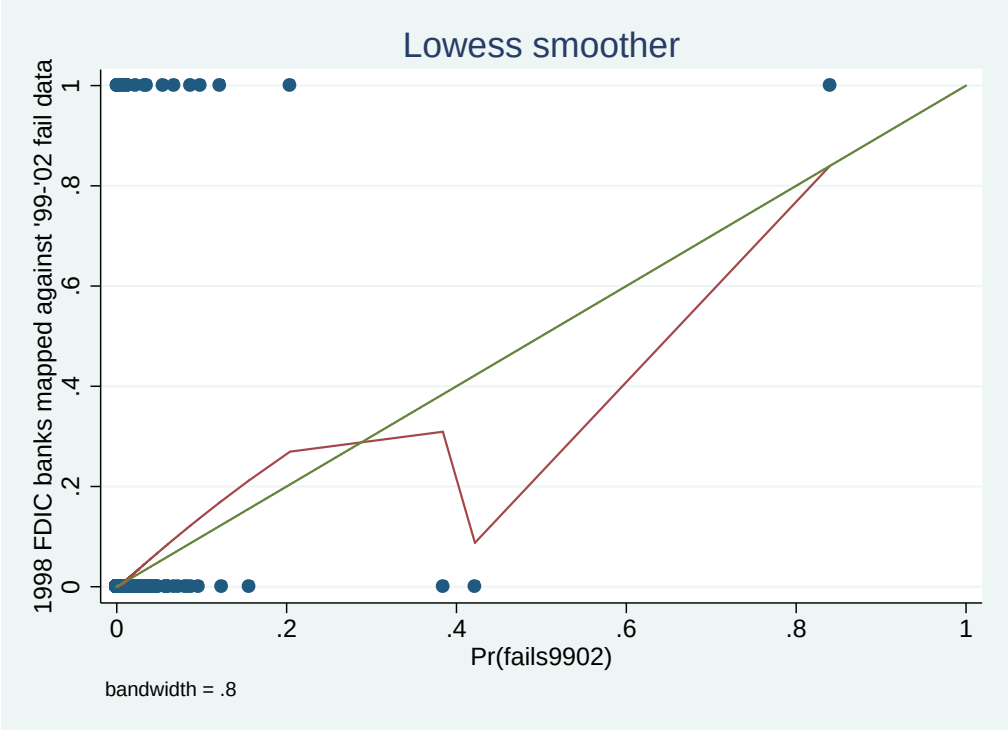


For the 1998 data, we observe a few banks that cluster around higher deviance residuals while the majority plots as predicted. For Pearson residuals, some banks present a deviating behavior but less clustering. For the 2008 data, we note that bank with cert 3,287 stands out from the crowd when we look at both the deviance

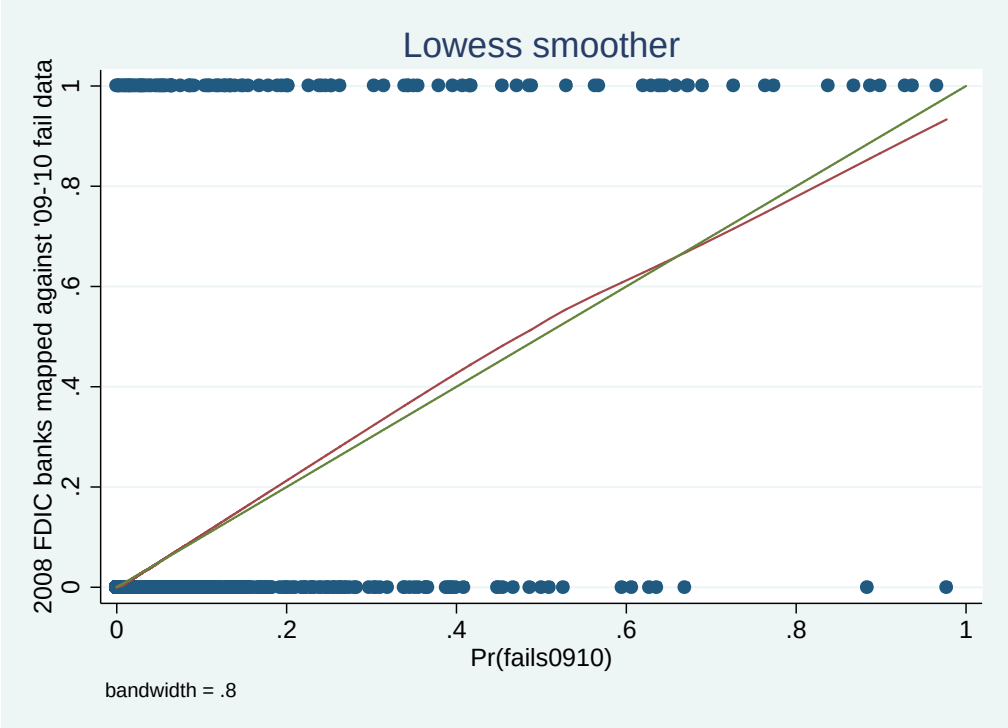
and Pearson residuals. The deviance residuals show more dispersion than the Pearson residuals but the vast majority of banks are plotted as predicted.

Testing the assumption of linearity

1998 data:



2008 data:



The graphs indicate a reasonably linear relationship for the 2008 data but not for the 1998 data. This is not surprising if we consider the relatively small set of defaults in 1999-2002 compared to 2009-2010.

Classification statistics

Logistic model for fails9902

	True		
Classified	D	~D	Total
+	1	0	1
-	23	9620	9643
Total	24	9620	9644

Classified + if predicted Pr(D) >= .5
True D defined as fails9902 != 0

Sensitivity	Pr(+| D)	4.17%
Specificity	Pr(-|~D)	100.00%
Positive predictive value	Pr(D| +)	100.00%
Negative predictive value	Pr(~D| -)	99.76%
False + rate for true ~D	Pr(+|~D)	0.00%
False - rate for true D	Pr(-| D)	95.83%
False + rate for classified +	Pr(~D| +)	0.00%
False - rate for classified -	Pr(D| -)	0.24%
Correctly classified		99.76%

Logistic model for fails0910

	True		
Classified	D	~D	Total
+	22	10	32
-	93	4969	5062
Total	115	4979	5094

Classified + if predicted Pr(D) >= .5
True D defined as fails0910 != 0

Sensitivity	Pr(+| D)	19.13%
Specificity	Pr(-|~D)	99.80%
Positive predictive value	Pr(D| +)	68.75%
Negative predictive value	Pr(~D| -)	98.16%
False + rate for true ~D	Pr(+|~D)	0.20%
False - rate for true D	Pr(-| D)	80.87%
False + rate for classified +	Pr(~D| +)	31.25%
False - rate for classified -	Pr(D| -)	1.84%
Correctly classified		97.98%

Empirical Fee Model Testing Appendix

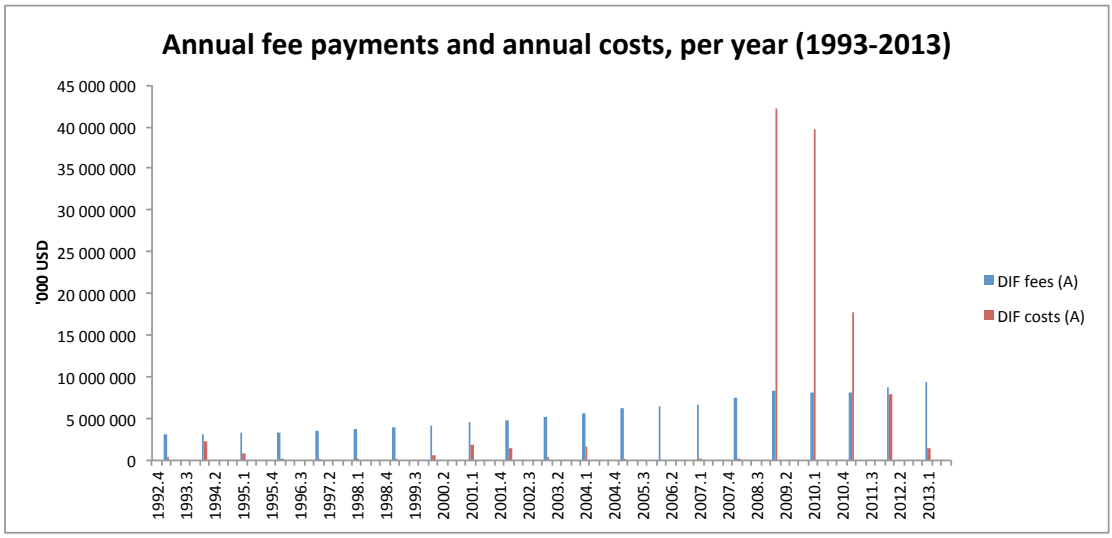


Figure A38. The chart displays the annual fee payments from banks to the U.S. deposit insurance fund as calculated by the current Swedish fee model and the actual historical costs incurred to the DIF on an annual basis. The period of measurement is 1993-2013.

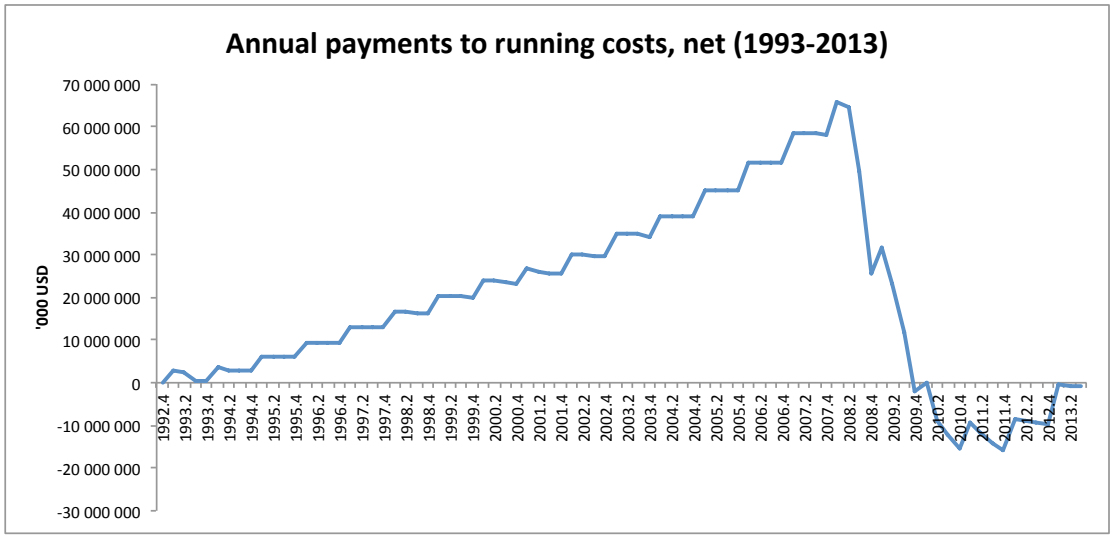


Figure A39. The chart displays the cumulative net of annual fee payments to the U.S. deposit insurance fund as calculated by the current Swedish fee model and costs to the DIF as they occur. The period of measurement is 1993-2013.

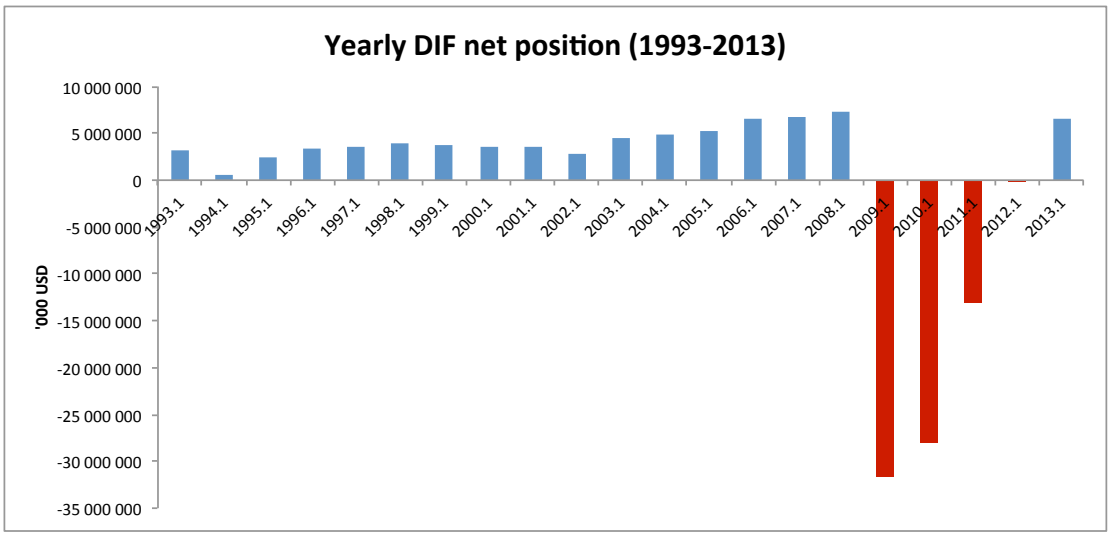


Figure A40. The chart displays the annual net of fee payments to the U.S. deposit insurance fund as calculated by the current Swedish fee model and costs to the DIF on an annual basis. The period of measurement is 1993-2013.

Simulation Model Appendix

Detailed description of simulation scenarios

- A one-year average PD scenario where banks default and move between brackets over one year as they have done on average during the period 1992-2012.
- A one-year minimum PD scenario where banks default and move between brackets over one year according to the year in the 1992-2012 period with minimum default incidence.
- A one-year maximum PD scenario where banks default and move between brackets over one year according to the year in the 1992-2012 period with maximum default incidence.
- A five-year average PD scenario where banks default and move between brackets as they have done on average during all five-year periods between 1992 and 2012.
- A five-year minimum PD scenario where banks default and move between brackets according to the five-year period between1992 and 2012 with minimum default incidence.
- A five-year maximum PD scenario where banks default and move between brackets according to the five-year period between 1992-2012 with maximum default incidence.

Scheme rest runs

SWE

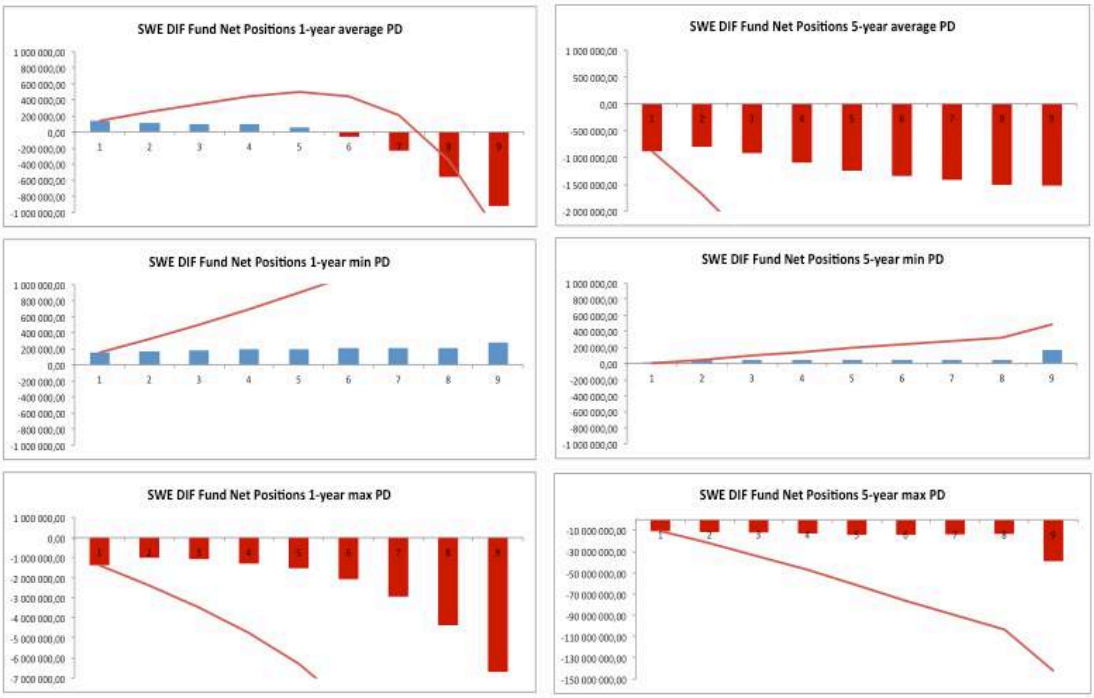


Figure A41. The chart displays the DIF net positions for the SWE model after each scenario test run, as specified in section 6.3 and above. The red lines indicate fund total nets and the bars represent per-bracket (1-9) nets.

ELP

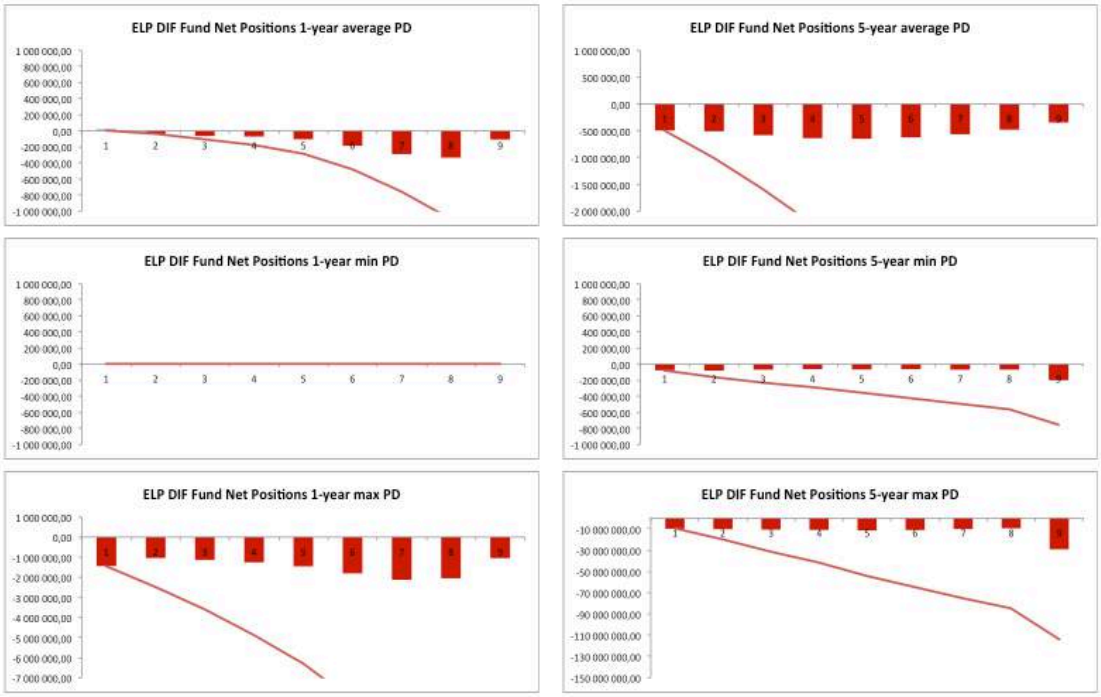


Figure A42. The chart displays the DIF net positions for the ELP model after each scenario test run, as specified in section 6.3 and above. The red lines indicate fund total nets and the bars represent per-bracket (1-9) nets.

UPD

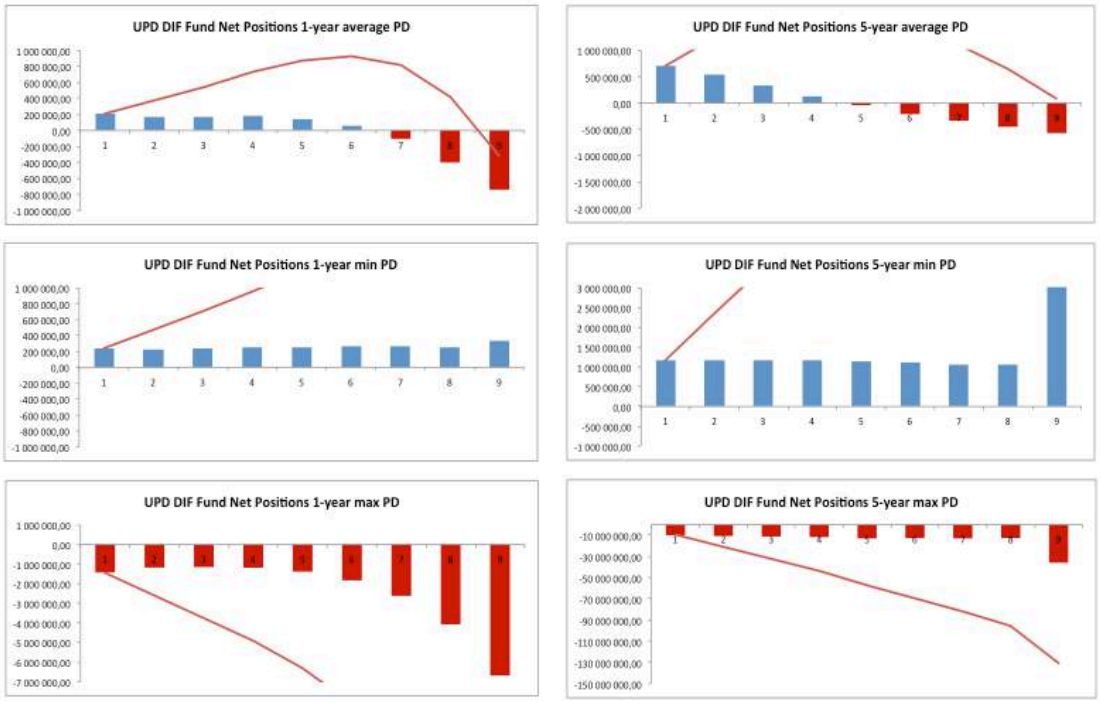


Figure A43. The chart displays the DIF net positions for the UPD model after each scenario test run, as specified in section 6.3 and above. The red lines indicate fund total nets and the bars represent per-bracket (1-9) nets.

Total DIF net comparison between models

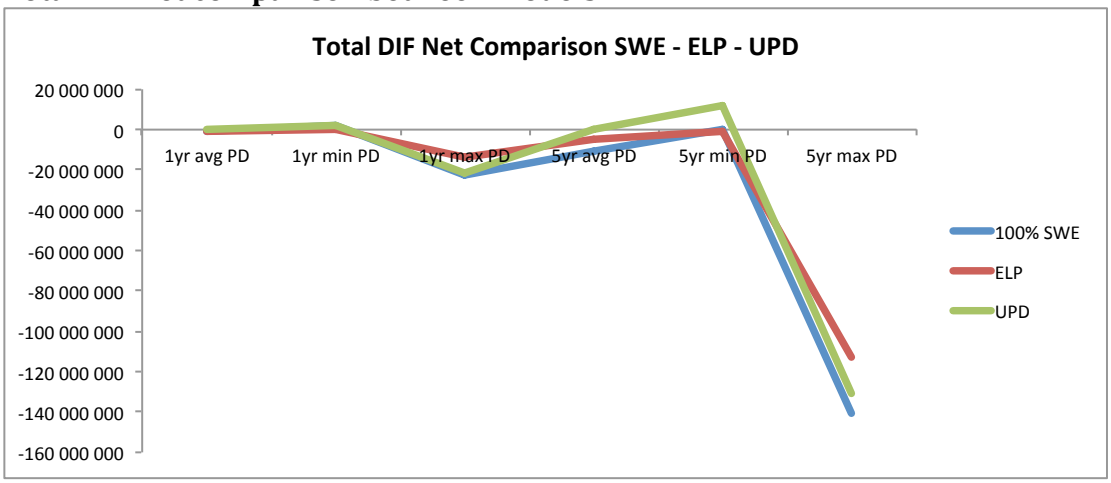


Figure A44. The chart displays the outcome of the scenario simulation testing on the three model specifications as described in section 6.3 and above. Each line represents a model specification, the scenarios are on the x-axis and the DIF net positions are on the y-axis.

Scenario	Total net		
	100% SWE	ELP	UPD
1yr avg PD	**-1 270 792**	**-1 206 521**	**-320 410**
1yr min PD	**1 800 000**	**0**	**2 330 900**
1yr max PD	**-22 369 908**	**-13 340 829**	**-21 814 147**
5yr avg PD	**-10 735 372**	**-4 886 590**	**82 977**
5yr min PD	**489 085**	**-755 377**	**12 128 405**
5yr max PD	**-140 858 418**	**-112 806 311**	**-130 926 299**

Table A3. The table displays the outcome of the simulation model testing for the three models SWE (real Swedish model), ELP (Swedish model with expected loss pricing) and UPD (Swedish model with additional parameters). Scenarios are run as specified in section 6.3.

Model components

PD matrixes

Average 1-year PD	Average 5-year PD
0,01%	0,58%
0,05%	0,51%
0,04%	0,55%
0,04%	0,68%
0,03%	0,87%
0,05%	1,20%
0,08%	1,72%
0,11%	2,34%
2,75%	4,66%

The PD matrixes above correspond to the average one-year and five-year default probabilities among bracket banks 1-9 over the period 1993-2013. They are obtained by estimating yearly transition matrixes for each of the years and then averaging across all. We have produced one matrix per year for both one- and five-year horizons.

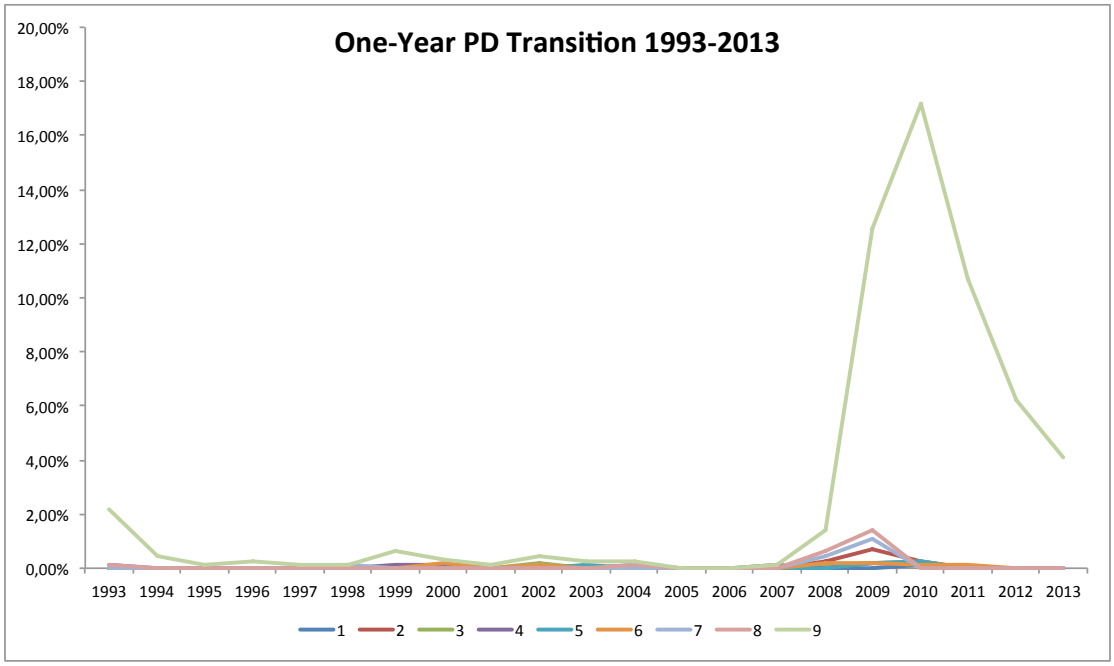


Figure A45. The chart displays the one-year PDs for each bracket group of banks estimated annually between 1993 and 2013. The one-year PD matrix above is made up of simple averages across all years for each bracket (line).

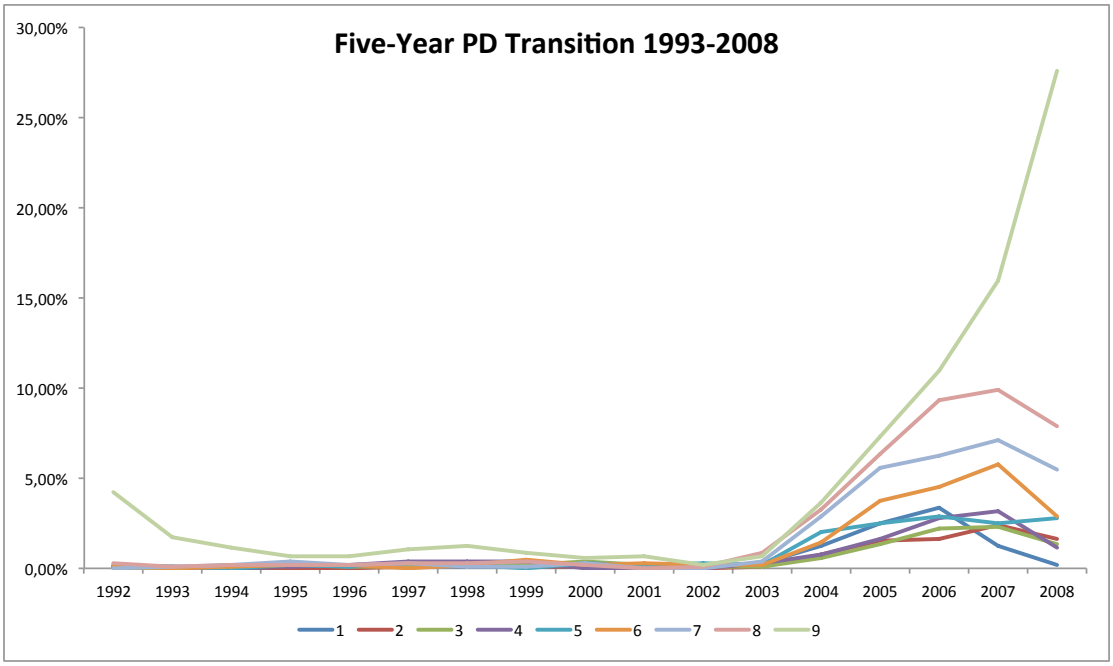


Figure A46. The chart displays the five-year PDs for each bracket group of banks estimated annually between 1993 and 2008. The five-year PD matrix above is made up of simple averages across all years for each bracket (line).

Transition matrixes

1-year Transition Matrix (%)									
Start brack	1	2	3	4	5	6	7	8	9
1	89,10%	11,60%	1,47%	0,65%	0,27%	0,23%	0,11%	0,09%	0,12%
2	9,35%	70,56%	16,35%	2,62%	1,14%	0,47%	0,44%	0,21%	0,18%
3	0,54%	15,12%	57,85%	19,42%	4,54%	1,73%	0,77%	0,49%	0,39%
4	0,38%	1,50%	19,25%	49,06%	20,32%	5,98%	2,30%	0,96%	0,73%
5	0,12%	0,51%	2,88%	21,36%	43,17%	21,71%	6,59%	2,55%	1,25%
6	0,19%	0,35%	1,06%	4,17%	22,33%	39,05%	22,04%	7,47%	3,17%
7	0,12%	0,12%	0,52%	1,48%	5,31%	21,99%	39,15%	22,61%	7,51%
8	0,07%	0,12%	0,29%	0,78%	1,86%	6,23%	22,12%	42,84%	24,33%
9	0,13%	0,11%	0,34%	0,47%	1,05%	2,61%	6,48%	22,78%	62,31%

5-year Transition Matrix (%)									
Start brack	1	2	3	4	5	6	7	8	9
1	69,98%	17,93%	6,92%	4,17%	3,49%	3,26%	2,93%	2,65%	3,23%
2	20,98%	41,11%	20,56%	9,90%	6,16%	4,18%	2,98%	2,58%	2,81%
3	4,20%	22,71%	28,24%	19,01%	11,90%	7,63%	5,06%	3,79%	3,67%
4	1,61%	9,05%	20,65%	22,56%	17,20%	12,52%	8,37%	6,08%	4,97%
5	0,98%	4,11%	11,37%	18,21%	19,13%	16,79%	12,78%	9,35%	7,61%
6	0,73%	2,22%	5,67%	11,47%	17,07%	18,24%	16,72%	13,60%	11,28%
7	0,53%	1,35%	2,92%	7,32%	11,85%	16,62%	19,15%	18,48%	15,31%
8	0,46%	0,77%	2,02%	4,44%	8,08%	12,17%	18,04%	22,17%	21,42%
9	0,52%	0,74%	1,66%	2,92%	5,12%	8,59%	13,97%	21,31%	29,70%

The transition matrixes above correspond to the average one-year and five-year transition patterns among bracket banks 1-9 over the period 1993-2013. They are obtained by estimating yearly tone- and five-year transition matrixes for each of the

years and then averaging across all. We have produced one matrix per year for both one- and five-year horizons.

LGD matrixes

LGD Matrix			
Bracket	**Mode distr.**	**5-yr distr.**	**Average distr.**
1	34,66%	36,39%	41,64%
2	26,94%	31,74%	28,00%
3	23,00%	29,28%	24,71%
4	31,22%	29,38%	33,96%
5	29,45%	30,06%	29,53%
6	26,73%	27,36%	32,75%
7	28,62%	27,56%	29,75%
8	29,33%	27,62%	28,96%
9	29,85%	30,46%	31,11%

These matrixes are used as input in the model to estimate the costs to the DIF as a default occurs. Each bracket bank has its own estimated LGD, as described in the Simulation Method section. For the simulations, an average of the three (*mode*, *5-yr* and *arithmetic average*) estimation methods is used.

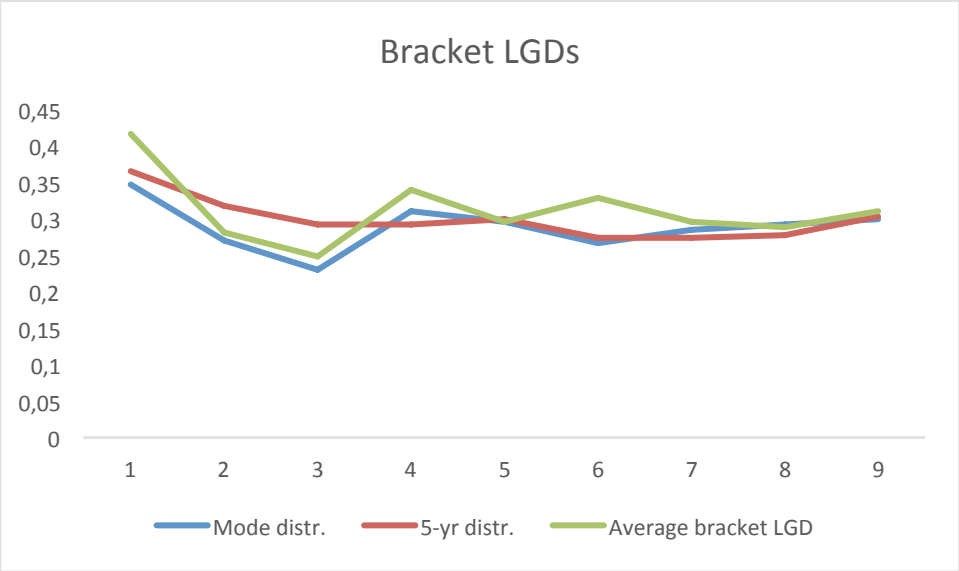


Figure A47. The chart displays the three different versions of LGD estimates across brackets 1-9. The practical application of the LGD variable in the models uses average LGD values derived from the three LGD estimations.

PD simulation module

Empirical defaults	
Start bracket	PD %
1	0,58%
2	0,51%
3	0,55%
4	0,68%
5	0,87%
6	1,20%
7	1,72%
8	2,34%
9	4,66%

Default Event Simulation Matrix	Start bracket								
	1	2	3	4	5	6	7	8	9
Bracket	1	2	3	6	4	6	2	7	8
ui	86,34%	57,06%	48,76%	24,01%	7,59%	38,84%	74,26%	17,74%	91,54%
Default	0	0	0	0	0	0	0	0	0

The PD module uses the PD matrix (one- or five-year) to estimate the number of defaults per bracket over the simulation run. Each bracket has its own column 1-9 where a uniformly random shock ui is measured against the PD value for each bracket (to the far left). For any case where the bracket ui value is below the bracket PD value, a default is registered and the corresponding cell on the row “Default” will turn from 0 to 1. The higher the PD is, the higher the likelihood of default over any 10,000 period run.

CAR simulation module

	CARsim	
Year	1997	RANDBETWEEN(1993;2013)
Row no.	742	RANDBETWEEN(1;780)

Bracket	CAR
1	0,3731871
2	0,2431111
3	0,198388
4	0,1840386
5	0,1584948
6	0,1490458
7	0,1393407
8	0,1179719
9	0,1092631

The CAR simulation module will randomly draw observations of CARs for a sample of banks from each bracket and year based on the cells *Year* and *Row no*. For instance, if the year is 1997 and the row is 742, CARs will be retrieved for each bracket from the column of year 1997 and row (observation) 742. As such, we are able to capture correlations between banks depending on the time of observation - CARs in 2009 looked very much different from 2005 etc.

Fee simulation components module

Determination of fees	
Annual total fee	180,00
a	0,5
b	0,78258935
c	5,6
LA fee	11,8362195
LB fee	14,0114908

top	low
252	108

All Guaranteed Deposits	WA_Output1	A_Output1
180000,00	0,77522401	0,77522401
139540,3221		

All Guaranteed	WA_Translated (should be 1.0)
180000,00	1,00000

Min	Max
0,7698562	1,1664014

Goal	Mult
1	1,28994972

The fee simulation proceeds in accordance with the process of determining the true Swedish deposit insurance fee as described in appendix section Swedish Fee Model Calculation.

Bank fee and bracket determination module

Bank details	1	2	3	4	5	6	7	8	9
Ins. Deps	20000	20000	20000	20000	20000	20000	20000	20000	20000
Bracket	1	2	3	6	4	6	2	7	8
Fee factor	0,6	0,7	0,8	1,1	0,9	1,1	0,7	1,2	1,3
CAR	0,373187098	0,2431111	0,198388	0,1490458	0,1840386	0,149045845	0,2431111	0,13934075	0,1179719
Int. Output	0,596810973	0,70057454	0,75765857	0,8396621	0,7792177	0,839662123	0,70057454	0,85863311	0,9042224
Car factor	0,76985615	0,90370593	0,97734146	1,0831219	1,0051517	1,083121923	0,90370593	1,10759355	1,1664014
Sim fee	15,39712301	18,0741186	19,5468292	21,662438	20,103034	21,66243846	18,0741186	22,151871	23,328029
ui	0,085411731	0,57444279	0,4560964	0,7931903	0,2615545	0,556244796	0,04642655	0,47393685	0,6423352
New bracket	1	2	3	6	4	6	2	7	8
New fee factor	0,6	0,7	0,8	1,1	0,9	1,1	0,7	1,2	1,3

The module above displays how the fees are determined for each bank. The first row states the amount of deposits, in this case the uniform USD 20,000. Bracket is determined according to the transition matrix input as described above. CAR is obtained from the CAR simulation module described above. Int. Output is a fee estimation function that derives from the components of the fee simulation module described above. CAR factor is Int. Output x the Mult factor in the fee simulation module. Sim fee is a function that determines the fee based on the CAR factor and the level of deposits. The *ui* is a uniformly random shock that plays a part in determining the bracket. New bracket is the bracket assigned to the bank before the next run. New fee factor takes a value between 0.6 and 1.4 depending on what bracket the bank belongs to.

Typical simulation output

	Start bracket								
Bracket Distributions	1	2	3	4	5	6	7	8	9
1	6 966	1 796	728	401	362	323	256	243	333
2	2 126	4 141	2 070	1 031	597	405	288	298	249
3	431	2 307	2 892	1 828	1 222	747	505	398	376
4	148	870	1 986	2 315	1 771	1 275	797	659	486
5	104	394	1 123	1 858	1 885	1 695	1 287	957	768
6	71	209	548	1 112	1 700	1 848	1 655	1 332	1 175
7	49	142	295	731	1 183	1 679	1 930	1 866	1 501
8	48	72	200	432	808	1 213	1 817	2 180	2 139
9	57	69	158	292	472	815	1 465	2 067	2 973
Stats									
Mean bracket	2	3	4	4	5	6	6	7	7
Total default costs	743 199,28	551 354,35	775 932,74	1 213 707,42	1 119 766,12	1 391 465,49	2 041 448,75	2 050 183,55	2 375 951,53
Average default costs	11 260,60	10 810,87	11 245,40	11 450,07	11 086,79	10 621,87	10 468,97	10 354,46	9 941,22
Fees paid	401 375,46	275 941,76	252 938,03	422 559,26	510 851,28	642 383,03	986 129,32	1 373 205,79	2 783 398,11
Net	-341 823,82	-275 412,59	-522 994,72	-791 148,16	-608 914,83	-749 082,46	-1 055 319,43	-676 977,75	407 446,58

	Start bracket								
DIF Funding	1	2	3	4	5	6	7	8	9
1	279 598,15	49 559,14	18 413,89	16 944,63	18 492,82	20 748,97	25 244,91	33 368,90	92 687,16
2	85 332,42	114 267,48	52 358,17	43 565,86	30 497,82	26 016,51	28 400,52	40 921,53	69 306,61
3	17 299,28	63 659,76	73 149,68	77 243,83	62 426,03	47 986,01	49 799,53	54 653,59	104 655,77
4	5 940,36	24 006,93	50 233,49	97 822,47	90 471,76	81 903,84	78 594,51	90 494,26	135 273,15
5	4 174,30	10 872,11	28 404,94	78 511,51	96 295,47	108 883,92	126 914,84	131 415,79	213 764,97
6	2 849,77	5 767,18	13 861,00	46 988,59	86 844,72	118 712,38	163 204,40	182 911,01	327 049,28
7	1 966,74	3 918,37	7 461,67	30 889,08	60 433,71	107 856,11	190 322,96	256 240,20	417 788,06
8	1 926,60	1 986,78	5 058,76	18 254,56	41 276,78	77 921,06	179 179,70	299 358,86	595 368,86
9	2 287,84	1 904,00	3 996,42	12 338,73	24 112,18	52 354,22	144 467,95	283 841,64	827 504,26

	Start bracket								
TWA Contribution from DIFs	1	2	3	4	5	6	7	8	9
1	517 712,62	99 023,24	56 487,90	48 669,67	40 535,53	44 944,34	52 261,09	49 819,46	79 119,19
2	158 004,17	228 315,84	160 618,08	125 133,23	66 850,04	56 354,35	58 793,72	61 095,47	59 161,19
3	32 031,89	127 197,45	224 399,75	221 865,72	136 835,42	103 942,47	103 093,16	81 597,31	89 335,78
4	10 999,35	47 967,83	154 100,24	280 973,27	198 310,58	177 411,85	162 703,47	135 107,10	115 471,24
5	7 729,27	21 723,36	87 137,25	225 506,84	211 075,91	235 853,40	262 734,45	196 202,57	182 473,08
6	5 276,71	11 523,31	42 521,11	134 964,26	190 360,24	257 142,82	337 859,77	273 084,45	279 174,30
7	3 641,68	7 829,23	22 890,02	88 722,01	132 468,33	233 627,06	393 999,61	382 564,25	356 630,32
8	3 567,36	3 969,75	15 518,65	52 432,16	90 477,10	168 784,76	370 931,24	446 940,01	508 216,03
9	4 236,24	3 804,35	12 259,74	35 440,26	52 852,96	113 404,44	299 072,24	423 772,94	706 370,39

Bracket distributions – shows how banks from each starting bracket 1-9 are distributed across brackets over the 10,000 simulation runs. This is directly linked to what transition matrix is used and patterns will shift both depending on what underlying matrix is used (what year and horizon) and on pure random selection of brackets.

Stats – describes some basic characteristics of the simulation run, such as the mean bracket for each bank, total default costs incurred per bracket, average default costs, total fees paid per bracket and the net position (fees less costs).

DIF Funding – shows from what brackets banks have paid funds. E.g. if a bank starts in bracket 1, transitions to bracket 2 and pays USD 100 in fee, this amount will count towards the total in the first column (start bracket 1) and second row cell (current bracket 2) and so forth.

TWA Contribution from DIFs – shows how default costs are allocated among brackets. If a bracket 1 bank defaults, and that bank has been in either or all of brackets 1-9 during its life, its total default costs will be drawn proportionally from each of the brackets visited by the bank over the run. E.g. if a bank starts in bracket 1 and stays there for 5,000 runs and then transitions to bracket 3 and stays there for 5,000 runs, it will pay fees as both a bracket 1 and 3 bank for an equal amount of

time. As it defaults, the resulting costs will be drawn 50/50 from the theoretical fund balances of brackets 1 and 3. I.e. funds to cover deposits for each bank are taken proportionally depending on time spent in each bracket. By using this procedure, we can observe what bracket banks bring in the most/least money to the DIF and also what bracket banks draw most/least funds from the DIF. In the end it will serve as a measure for how well fees are differentiated among banks according to their perceived contribution and cost tendencies.

Net positions as shown in the graphs in the scheme test run section above are obtained by summing over each row in the matrix "DIF Funding" and "TWA Contribution from DIFs" and subtracting the second from the first on a row-to-row basis. This will give nine nets, one for each bracket, which is displayed graphically.

Backtracking Appendix

Recap: Based on these bracket scores, we calculate a standardized and a non-standardized cost and fee payment time for all banks. In the standardized measure, we assume all banks are of equal size and calculate (1) the amount of time each bank spend paying in which bracket before default, and (2) the product of percentage loss given default divided by brackets. We then do the same for non-standardized data, (3) the fees depending on deposits guaranteed and the (4) costs on realized losses in dollars.

Deeper: We look at (1) so as to see how fees are spread. If a bank is in a certain bracket for x years, then it will pay the fees corresponding to this bracket. Therefore, by seeing how many years default banks spend in each bracket, we can obtain time-weighted average fee payments split by the brackets they have belonged to historically. This will aid in aligning the fees overall since ideally all brackets in- and outflows of funds should balance.

A simple overview shows that banks move up brackets gradually as the time of default approaches. The delta values become more pronounced in the last couple of years, especially in the last year. This would imply a large deterioration outside of the normal occurring for banks close to default, which is reasonable, given that default is hardly planned. Part of this effect could be because a lot of defaults happen around financial crises, when deterioration is strong – but because these values are relative values (brackets are relative to other banks) the effect of large external shocks should not be so large.

The results also indicate that banks that subsequently default are in the long run quite normal. The years farthest away have a low number of observations, but the trend of long-term normality is clear. However, results exhibit noticeably above normal weakness already more than 10 years before default, on average. This shows a relative stability in the system and that long term perspectives can be useful. If banks were only a short time in crisis before defaulting, this would imply that differentiating fees would not be very helpful. It would only serve to punish those banks that suffered very large negative shocks. Here, however, we can see that defaulting banks often have insignificant capital over long periods. Therefore, differentiation of fees makes sense.

We calculate a quotient between the lowest bracket and all the other ones, representing the difference in bank years spent paying into these brackets. This

measure is simply meant to make the differences between brackets more easy to understand.

It turns out that the shorter the perspective, the more pronounced the difference in this quotient, ranging from about 6 for 15 years, to 27 for 3 years. We redo these calculations adding a real return quotient. The real return represents the expected return that a deposit insurance institution can obtain on its funds by investing them in the S&P 500.[48] This amounts to approximately 6% for the 1992-2013 period. These new calculations balance bracket contributions further, since periods farther away, when bracket distribution is evener, are weighted up. Our results clearly show that looking at bank characteristics at the time of failure is not the way to achieve fairness in the fee setting. Observe, however, that fees will in the end come from all banks, not only from failing banks. Costs will however come mostly from failing banks (and from administration of the deposit insurance).

These findings show that failing banks will spend more time in high-risk categories over time. This proportion falls from a quotient of 27 to 1 from the highest to the lowest at the three-year horizon to a mere 6 in a 15-year horizon. Firstly, this shows clearly that time horizon matters when looking at our funding model fairness. A certain distribution of fees will thus be fair over a given time horizon – which means regulators must choose a time horizon over which to maximize fairness. The differences are strikingly large, especially accounting for returns on early fees. These results show the consequences of choosing different time horizons, and serve as a guidance to decision makers.

The second measure (2) is an application of the LGD averages to standardized banks. It shows a slightly less pronounced curve, losses for standardized banks divided with quotients from around 22 to 5. One reason for looking at the standardized bank size model is that outliers like very large banks have little effect here. While large outlier banks are of special importance to the system anyway, the deposit insurance system has often found itself incapable of coping with these anyway, relying on extra funds like the stability fund. Therefore, the largest banks are hard to treat in this context. The standardized system could also make differences in the structure of American and Swedish bank markets less important. The American has a very different structure, with many more actors of

[48] http://www.bogleheads.org/wiki/S&P_500_index

very different sizes, whereas the Swedish one is more consolidated. This measure thus provides results that are not affected by such differences.

Looking at real deposits (3) provides the dollar-weighted time banks spend in each payment bracket. It thus looks both at how much insured funds were in different brackets at different time horizons and at the costs of failing banks at insuring themselves. This could be explained by the fact that banks which fail might do so after only a limited period in bracket nine, while they might linger longer in bracket eight before that. Data supports this, which details that banks move through brackets very quickly just before failure.

Finally, looking at losses (4), we get the exact distribution of costs among brackets for different time horizons. We see that if we divide costs of default over a three-year horizon, categories 8 and 9 get more than 90 times higher costs than category 1, while over a 15-year horizon, without taking interest rate growth into account, we see 30 and 42, respectively.

15 YEAR HORIZON					
STANDARDIZED SIZED			ACTUAL SIZE		
1. Fee years		**Quotient**	**3. Fee base $**		**Quotient**
1	3.92%	1.00	13,294,161.40	0.75%	1.00
2	6.15%	1.57	24,945,796.73	1.40%	1.88
3	5.70%	1.45	21,618,608.27	1.21%	1.63
4	6.62%	1.69	18,432,648.27	1.03%	1.39
5	8.84%	2.25	41,973,583.27	2.36%	3.16
6	11.09%	2.83	81,594,497.93	4.58%	6.14
7	13.85%	3.53	272,359,083.20	15.29%	20.49
8	17.35%	4.42	606,176,522.47	34.03%	45.60
9	26.48%	6.75	700,755,271.87	39.34%	52.71
2. Stand. Costs		**Quotient**	**4. Actual Costs**		**Quotient**
3.99	5.10%	1.00	468,579.13	0.67%	1.00
5.25	6.70%	1.31	1,152,541.67	1.65%	2.46
4.50	5.75%	1.13	1,361,217.93	1.95%	2.90
5.65	7.21%	1.42	4,626,274.47	6.63%	9.87
7.32	9.34%	1.83	7,566,758.73	10.85%	16.15
8.64	11.03%	2.16	8,740,580.27	12.53%	18.65
10.48	13.38%	2.63	11,737,716.27	16.83%	25.05
12.24	15.62%	3.07	14,100,327.27	20.21%	30.09
20.27	25.88%	5.08	20,003,784.80	28.68%	42.69
1.b fee + interest		**Quotient**			
4.49%	0.06968	1.00			
6.63%	0.102936	1.48			
5.93%	0.091999	1.32			
7.00%	0.108637	1.56			
9.08%	0.140868	2.02			
11.25%	0.174636	2.51			
13.65%	0.211857	3.04			
17.10%	0.265271	3.81			
24.87%	0.385847	5.54			

Table A4. This is the 15-year horizon, the longest for which we backtrack. The quotient to the right shows the relation between brackets 1 and the others. This represents only the population of default banks. Maybe the most interesting is part 4. Actual Costs, that shows that the difference between the highest and lowest brackets is almost at 43, while the Swedish fee model allows for at most 2.33. This is quite a big difference, even considering the long horizon.

10 YEAR HORIZON					
STANDARDIZED SIZE			ACTUAL SIZE		
1. Fee years		**Quotient**	**3. Fee base $**		**Quotient**
13.2	3.48%	1.00	29,255,910.70	1.58%	1.00
17.6	4.64%	1.33	14,982,018.30	0.81%	0.51
20.3	5.36%	1.54	19,296,909.30	1.04%	0.66
21.2	5.59%	1.61	15,771,786.80	0.85%	0.54
30.6	8.07%	2.32	58,091,974.50	3.15%	1.99
41.3	10.90%	3.13	103,522,563.60	5.61%	3.54
54.8	14.46%	4.15	389,261,941.40	21.08%	13.31
69	18.21%	5.23	695,654,062.90	37.67%	23.78
111	29.29%	8.41	520,969,361.50	28.21%	17.81
2. Stand. Costs		**Quotient**	**4. Actual Costs**		**Quotient**
4.40	4.10%	1.00	614,639.20	0.76%	1.00
5.33	4.97%	1.21	1,118,709.20	1.38%	1.82
5.70	5.31%	1.30	1,619,207.30	2.00%	2.63
6.32	5.90%	1.44	4,883,739.00	6.04%	7.95
8.88	8.28%	2.02	9,027,884.80	11.17%	14.69
11.69	10.90%	2.66	8,849,166.60	10.95%	14.40
14.99	13.97%	3.41	14,888,980.70	18.43%	24.22
18.09	16.86%	4.12	18,982,383.50	23.50%	30.88
31.87	29.71%	7.25	20,807,130.70	25.75%	33.85
5 YEAR HORIZON					
STANDARDIZED SIZE			ACTUAL SIZE		
1. Fee years		**Quotient**	**3. Fee base $**		**Quotient**
11.4	2.29%	1.00	18,211,127.00	0.97%	1.00
17.2	3.46%	1.51	15,369,465.40	0.82%	0.84
22	4.43%	1.93	31,367,702.20	1.68%	1.72
24.2	4.87%	2.12	9,593,895.60	0.51%	0.53
36.4	7.32%	3.19	68,064,587.60	3.64%	3.74
44.6	8.97%	3.91	93,678,941.60	5.00%	5.14
69.8	14.04%	6.12	370,185,159.20	19.77%	20.33
93.4	18.79%	8.19	545,752,779.00	29.15%	29.97
178	35.81%	15.61	719,793,648.40	38.45%	39.52
2. Stand. Costs		**Quotient**	**4. Actual Costs**		**Quotient**
4.03	2.79%	1.00	380,615.00	0.43%	1.00
4.90	3.39%	1.22	893,467.20	1.00%	2.35
6.26	4.34%	1.56	1,574,120.60	1.76%	4.14
7.52	5.21%	1.87	2,504,807.60	2.80%	6.58
10.57	7.32%	2.62	11,266,335.60	12.62%	29.60
12.14	8.41%	3.01	7,736,312.40	8.66%	20.33
19.97	13.83%	4.96	14,572,638.60	16.32%	38.29
26.05	18.04%	6.47	24,335,278.60	27.25%	63.94
52.98	36.69%	13.16	26,043,762.40	29.16%	68.43

Table A5. This is the 10- and 5-year horizons. The quotients to the right show the relation between brackets 1 and the others. This represents only the population of default banks. The most interesting is part 4. Actual Costs. The others are standardized forms.

3 YEAR HORIZON						
STANDARDIZED SIZE			ACTUAL SIZE		
1. Fee years		**Quotient**	**3. Fee base $**		**Quotient**
8.67	1.60%	1.00	10,348,388.33	0.55%	1.00
14.33	2.64%	1.65	18,928,658.33	1.01%	1.83
22.00	4.05%	2.54	28,042,541.00	1.49%	2.71
25.67	4.73%	2.96	7,431,311.33	0.40%	0.72
30.33	5.59%	3.50	84,404,377.67	4.50%	8.16
39.67	7.31%	4.58	110,121,628.67	5.87%	10.64
73.33	13.51%	8.46	418,303,649.67	22.28%	40.42
95.00	17.50%	10.96	746,061,351.00	39.74%	72.09
234.00	43.09%	27.00	453,860,632.00	24.17%	43.86
2. Stand. Costs		**Quotient**	**4. Actual Costs**		**Quotient**
3.08	1.92%	1.00	314,977.67	0.34%	1.00
3.58	2.23%	1.16	514,738.00	0.56%	1.63
6.63	4.12%	2.15	1,379,951.33	1.51%	4.38
8.27	5.14%	2.68	1,367,906.33	1.50%	4.34
8.77	5.45%	2.84	8,405,522.00	9.19%	26.69
10.75	6.68%	3.48	3,159,805.67	3.46%	10.03
21.85	13.58%	7.08	17,236,484.67	18.85%	54.72
27.55	17.13%	8.93	28,645,412.00	31.33%	90.94
70.37	43.75%	22.82	30,398,867.33	33.25%	96.51
1.b fee + interest		**Quotient**			
100.00%	1	60.33			
245.97%	2	148.40			
290.50%	3	175.27			
987.30%	4	595.68			
1614.83%	5	974.29			
1865.34%	6	1125.44			
2504.96%	7	1511.35			
3009.17%	8	1815.56			
4269.03%	9	2575.68			

Table A6. This is the 3-year horizon, the shortest for which we backtrack. The quotient to the right shows the relation between brackets 1 and the others. This represents only the population of default banks. The most interesting is part 4. Actual Costs. The others are standardized forms.