Contagion without deposit insurance: The South African small bank crisis of 2002/3

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Abstract

Following the failure of Saambou bank in February 2002, another seven South African banks failed within a month, including the fifth-largest, and a further five within a year. In total, twenty-two small and mid-sized banks deregistered over two years: half the total number of banks, and nearly 10 per cent of the deposit base. South Africa is one of the few jurisdictions that does not have a explicit deposit insurance scheme. While such a scheme may have prevented the first failure, I show that it would not have prevented contagion. The banks that failed were all well capitalised and solvent, but had relatively high levels of short-term funding from non-bank financial institutions. They would not have qualified for a retail deposit insurance scheme, and would still have experienced a run of non-bank funding. This highlights that deposit insurance is best seen as a tool that should be used for its stated purposes (protecting vulnerable depositors), and not as a general financial stability tool that can prevent contagion. Indeed, if agents expect that the authorities will use deposit insurance to 'bail-out' a bank, this would introduce moral hazard.

1 Introduction

Deposit insurance ostensibly reduces the risk of a disorderly bank run (Diamond and Dybvig, 1983). But, by reducing the incentives for depositors to monitor banks it may have the opposite effect, introducing moral hazard. Moreover, deposit insurance has complex political and systemic implications (Calomiris and Jaremski, 2016). In short, ever since its widespread introduction, the contradictory effects have complicated any analysis of bank contagion episodes.

Almost uniquely, South Africa does not have an explicit deposit insurance scheme. Indeed, at the time of the small bank crisis of 2002/3, it had no framework for depositor protection at all – explicit or implicit. This presents unique relatively modern-day opportunity to analyse contagion absent deposit insurance.

The small bank crisis of 2002/3 began with a run on Saambou bank, then South Africa's seventh-largest. In the second half of January 2002 alone, Saambou's retail deposits fell R861 million – 8.8 per cent of all the banks retail deposits, and 5.6 per cent of its liabilities.[1]

[1] Unless otherwise indicated, the data for this section was obtained from the data sets described in

Estimates vary, but between the start of the run in mid-January and curatorship five weeks later, total outflows were nearly 20 per cent of Saambou's deposits.[2]

The proximate trigger of the run was the announcement on 15 January 2001 by South Africa's then largest bank, ABSA, of significant losses in its microlending subsidiary Unifer. Unifer's non-performing loan provisions were increased by R1.78 billion. The net effect was a R1.045 billion reduction in ABSA's capital, approximately 10.9 per cent of its capital base.[3] Saambou had a very similar clientele to Unifer, suggesting depositors were concerned about 'common exposures.'[4] Saambou had grown rapidly – assets grew by 34.8 per cent in 1999 alone – mainly in unsecured lending.

Table 1: Deposit balances, individuals, Saambou, R bn

Rbn			**Term**			**Outflow**	**(%*)**
	Cash	Short	Medium	Long	Total		
31-Dec-2001	0.499	1.268	0.018	8.007	9.792		-
31-Jan-2002	0.524	1.234	0.028	7.145	8.932	-0.861	-5.6%
Conclusion	0.524	1.234	0.028	5.033	6.820	-2.973	-19.2%

* Percentage of deposits *Source:* Bank Supervision monthly statistics

The run was concentrated amongst informed depositors with large balances, who declined to roll over their long-term deposits when the notice period expired. The effect was the same as that of a run, with long-term deposits falling quickly (see Table 1).[5] To cover the gap between its assets and liabilities, Saambou accessed interbank funding. Interbank deposits rose from R247 million to R1.027 billion, an increase of R782 million, suggesting it obtained money from another bank to make good the shortfall.[6] Liquidity moved in the

section 5 below. The exact scale of the run between the end of January and the curatorship a week later is difficult to determine precisely. This is because the bank's deposits were initially frozen, and then limited withdrawals were allowed.

[2]At the conclusion of the curatorship in August, individual deposits were R6.82 billion, suggesting the five-week run could have been as large as R2.9 billion, or 19.2 per cent of Saambou's total deposits (see Table 1). Press reports variously state that the run was between R1 billion and R2 billion.

[3]The sudden impact of the news caused ABSA shares to fall by 21 per cent over the course of the day, ultimately closing 16.4 per cent weaker. The banking sector as a whole fell 5.2 per cent. Sanlam, at that stage a 22.8 per cent shareholder in ABSA, fell 5.2 per cent.

[4]In contrast to Saambou, Unifer was almost exclusively a microlender, but both had been persistently understating their losses.

[5]Press reports indicated that the run began with a run on attorney trust funds. Lawyers evidently had had heard rumours that the bank was in difficulty. However, the data neither confirms nor counteracts this claim. Outflows were concentrated in the 'individuals' depositor category (line 23 of the DI-900 bank statistics). Attorneys hold trust money on behalf of individual clients and so for recordkeeping purposes, they appeared to be treated as individuals.

[6]Matching data from other banks shows that it was most likely FirstRand, which saw a large increase in exposures to other banks over the month (more than R1.44 billion). Surprisingly, it does not appear to be Investec, which at the time owned 41 per cent of Saambou through Fedsure.

system from Saambou to larger banks.[7]

From Monday, 4 February 2002, the Saambou share price began to fall rapidly. On Wednesday, 6 February, the intraday share price declined by 46 per cent. It recovered slightly, but ended the day 23 per cent lower. Saambou, however, faced continued deposit outflows and its liquidity position became almost impossible to sustain. It was clearly accessing lending from other banks to cover the shortfall, and these banks were increasingly reluctant to provide liquidity.

During the course of the week, Investec, the largest shareholder, proposed a bail-out package to the authorities, which the authorities declined (Mittner, 2003*a*). By the end of the week, the bank's financial position became impossible to sustain. The curatorship (statutory management) of the bank was announced by Trevor Manuel, the then Minister of Finance on Saturday, 9 February 2002.

1.1 Contagion[8]

1.1.1 The first wave: Sharp runs in March/April 2003

The Saambou curatorship announcement triggered concerns about other small banks. Following the announcement, seven banks immediately experienced runs: BOE Bank, Merrill Lynch, TA Bank, Cadiz, FirstCorp, PSG Investment Bank and International Bank. These banks collectively made up approximately 6.6 per cent of total deposits as at February 2002, with BOE alone comprising 6.5 per cent of deposits.

The BOE run was the most serious. Between the beginning of February and the end of June 2002, BOE liabilities shrank by R8.5 billion, or 17.9 per cent. Of this outflow, the largest was by individuals, who withdrew R5.5 billion, followed by other private sector financial institutions, which withdrew R4.5 billion. As with Saambou, BOE accessed interbank funding to make up the shortfall – interbank deposits rose by R3.5 billion. There were net small outflows in other categories.

The authorities provided emergency liquidity assistance to BOE to stabilise the system. A full guarantee of all its assets was provided to BOE on 14 March 2002. BOE was able to continue operating albeit in substantial distress, while a purchase and assumption agreement was negotiated with Nedbank. It was ultimately absorbed into Nedbank, and it deregistered a year later.

[7]At an aggregate level there was a small decrease in deposits by individuals of R1.6 billion. This was approximately 1 per cent of total individual deposits of, which totaled R158 billion. Total deposits (including individuals, government, corporations, etc.) actually increased substantially by R22.9 billion, more than half of which was as a result of an unexpected increase in deposits by other private sector financial institutions of R13.7 billion.

[8]Contagion is defined following Iyer and Peydro (2011) that '[t]here is contagion if the failure of a bank causes a significant negative externality to other banks'.

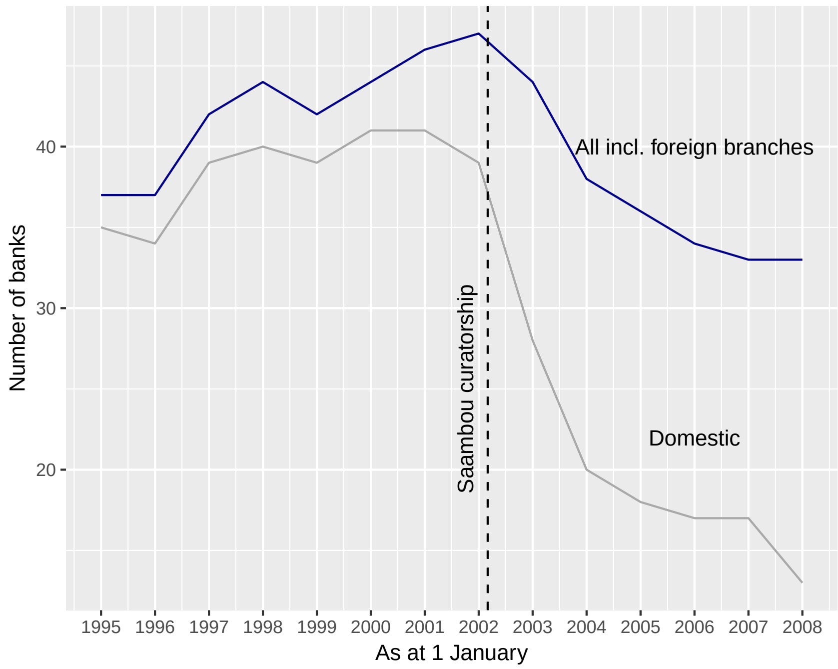


Figure 1: Number of banks, 1994 - 2008

The number of South African registered banks, mutual banks and foreign banks first increased following liberalisation from 1994. However, the Saambou curatorship (dotted line) precipitated a substantial consolidation.

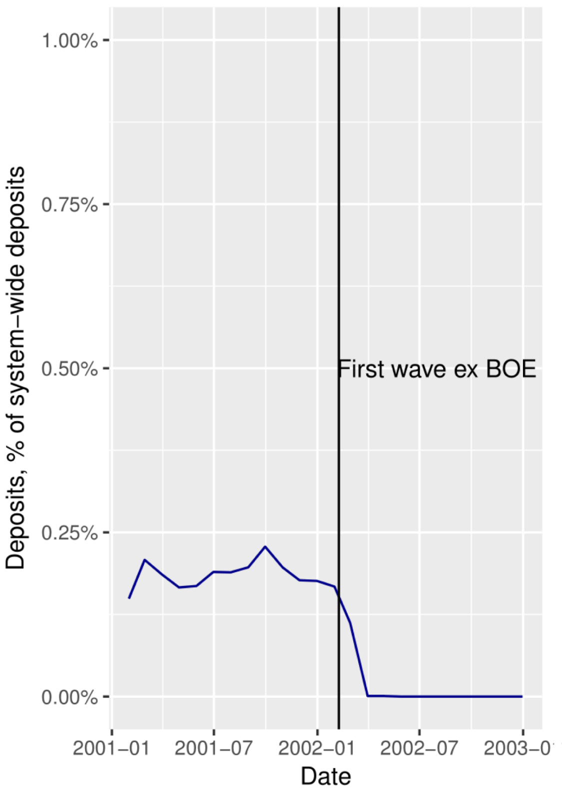
Source: Bank Supervision Department, Annual Reports

At the same time as the run on BOE, the other six banks also experienced runs. At the time, these banks made up 0.11% of the total systemwide deposits. Their entire deposit base was impacted by the run, and by the end of March 2002, the combined deposit base of these banks was nearly zero, as shown in the left-hand panel of Figure 2. With the exception of PSG Investment Bank, all these banks deregistered during the course of April 2002.[9]

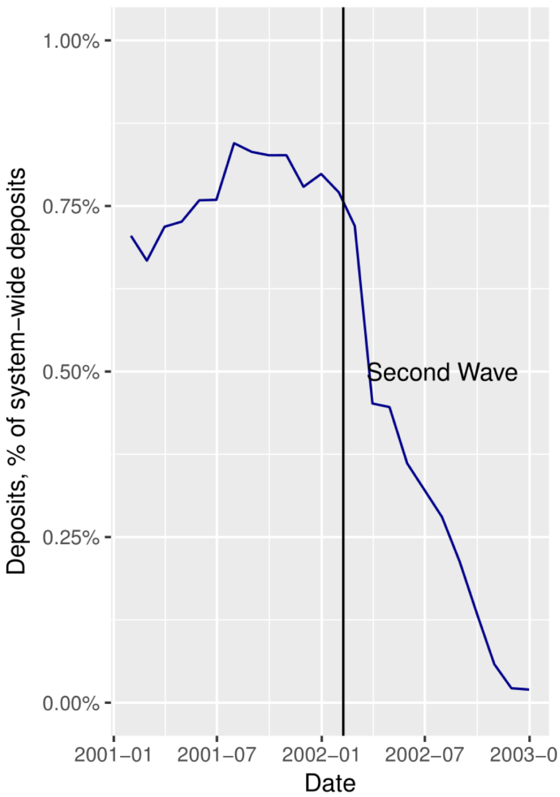
1.1.2 The second wave: Slow runs in September 2002 to February 2003

A second wave of bank cancellations took place between September 2002 and February 2003. These banks had significant shareholders and diversified businesses. However, they were not able to counteract the liquidity pressures in the market at the time, and a general loss of confidence.

[9] As noted in Table 2, PSG Investment Bank deregistered officially a year later, in April 2003. This was due in part to the attempted restructuring of the bank by a larger group; actions included buying Real Africa Bank. However, because it was affected by the run, it is counted as part of this group.



(a) Banks that deregistered during the 'First Wave,' i.e. April 2002.



(b) Banks that deregistered during the 'Second Wave,' i.e. October to Dec 2002.

Figure 2: Deposits, failed banks, % system-wide deposits

The 'First Wave' of affected banks saw sharp outflows, while the 'Second Wave' of affected banks saw large, but slightly more gradual declines in their deposit base. Both waves, however, were already experiencing outflows by the time Saambou failed. The vertical line indicates the date of the Saambou curatorship.

Brait Bank cancelled its licence on 30 September 2002, having given shareholders notice of its intention to cancel already in May 2002. It used the period between May and September to slowly wind up the banking business and restructure its assets into a new financial services company (ING Barings, 2002).

The next banks to fail were Corp Capital (29 November), Old Mutual Bank (17 December) and SECIB (end of December). All of these banks experienced depositor outflows as confidence dissipated. The final bank in this group was Unibank. Its depositor behaviour was somewhat unique. It had experienced a short sharp outflow of half of its deposits in April 2002, before briefly stabilising. Over the next year, there appears to be a slow outflow of the remaining liabilities and the bank became increasingly unsustainable, leading to its winding up. It deregistered on 31 March 2003.

Table 2: Timeline of cancellations and curatorships

Date	**Affected bank**	**% deposits (at Feb 2002)**
Jan 2002	Unifer announces large loss	
Feb 2002	Saambou*	2.30%
First wave		
Sharp runs		
Mar 2002	BOE**	6.51%
Apr 2002	Merrill Lynch, TA Bank, Cadiz, FirstCorp, International Bank, PSG Inv Bank***	0.11%
Second wave		
Slow runs		
Sep 2002	Brait Merchant Bank	0.16%
Nov 2002	Corpcapital	0.15%
Dec 2002	Old Mutual Bank	0.04%
Feb 2003	SECIB Bank	0.02%
Mar 2003	Unibank	0.34%
	Cumulative	*9.63%*
Third wave		
Consolidation		
Feb 2003	Nedcor Investment and Cape of Good Hope incorporated under Nedbank licence†	
July 2003	ING Bank and Rand Merchant Bank deregister	
Sept 2003	African Merchant Bank deregisters	

This table reflects the dates of curatorship or deregistration, not the date that runs began. In most cases, runs on these banks began earlier. In some cases, liabilities began shrinking before the Saambou collapse. For this reason, a more accurate dating technique is provided in Table 5.
* Saambou was placed into curatorship on 9 February 2002. Deregistration only occured towards the end of 2003, once the bank had been fully wound up.
** BOE was given a full going concern guarantee plus emergency liquidity assistance on 14 March 2002. Deregistration, however, only occured in March 2003 when the bank merged with Nedbank.
*** PSG Investment Bank was restructured as part of a comprehensive restructuring of the PSG group. It only formally deregistered in April 2003. For a discussion, see PSG Limited (2003).
† See discussion in section 1.1.3

Source: Annual Report of the Registrar of Banks, 2002 and 2003

1.1.3 The third wave: consolidation and clean-up, February 2003 onward

From February 2003, a further set of banks closed, either through mergers with larger banks or by cancelling their licences. Many of these deregistrations reflected the final winding-up of banks that had experienced runs in 2002. The Registrar of Banks argues in his 2003 Annual Report that these were not runs *per se*, but rather a residual consolidation, and so are not included in the empirical analysis below. The period is best characterised as the 'clean-up' period. On 21 February, Nedbank absorbed the banks it had purchased during 2002 and rationalised the number of bank licences the group held. The affected entities were Nedcor Investment Bank, Cape of Good Hope Bank and BOE Bank, all of which had already been operating under the control of Nedbank. In particular, as discussed above, BOE Bank had been rescued by Nedbank and the deregistration was a formality. The final three deregistrations were merely closures: ING decided at an international level to restrucutre and close, deregistering on 7 July; Rand Merchant Bank became a division of FirstRand on 28 July and African Merchant Bank closed on 30 September.

A full timeline of failed banks is provided in Table 2. In Table 5, I provide a more accurate dating technique, which is discussed below.

1.2 The research question

In the context of drawing lessons, the primary research question in this article is: why did some banks experience runs and others not? Would deposit insurance have protected them? A closely related secondary research question is: of those banks that failed, why did some experience slower runs than others? To answer the question, the paper exploits a firm-level data set of 244,776 observations, made up of detailed balance sheet data for 47 banks over a 24 month period. The next section discusses the contribution to the existing literature, followed by the methodology used, data and results.

2 Contribution to the literature

Measured by number of bank failures, the 2002/3 crisis is arguably the most significant banking episode in South African economic history.[10] To my knowledge, there has been no systematic evaluation of the crisis.[11]

The crisis is notable for the lack of any direct interconnectedness between the failing banks. There is a large literature arguing that contagion arises because of interconnectedness (see, for example, Allen and Gale (2000), Haldane and May (2011), or Acemoglu et al. (2015)) and overlapping exposures (as in Nier et al. (2007), Gai et al. (2011), Haldane and May (2011) and Glasserman and Young (2015)). The empirical analysis reveals that the failing banks had relatively low interbank exposures. They had no direct interconnectedness with Saambou (e.g. through overlapping claims). An alternative proposed in the literature is that of 'common exposures' (Ahnert and Georg, 2018), where runs occur on banks with similar assets. However, as will be demonstrated, the loan types of the banks that failed were no different from those that did not.

[10]The only episode of similar scale is the bank panic of the late 1800s, described in detail by Arndt (1928). There was a small bank crisis in the mid-1970s, described by Stephen Koseff in his MBA thesis, Koseff (1984)

[11]There is some limited discussion of it in Jones (2003), Verhoef (2009) and Gilbert et al. (2009). Mbuya (2003) usefully summarises press reports charting the rise and fall of Saambou (albeit with no discussion of the knock-on effects). Van Tonder (2006) considers the event from a human resources perspective and includes substantial detail on the events before and during the curatorship.

A further point of interest is the rich information set, which was available to depositors *ex ante*. Monthly data published at bank-level was available, including on solvency, liquidity, balance sheet structure and other variables. In the absence of interconnectedness, the theory posits that asymmetric and incomplete information can trigger contagion. Information-based runs arise because of information asymmetries (see Calomiris and Gorton (1991)). This, in turn builds on Diamond and Dybvig (1983), who argues that depositors with incomplete information run. Similar findings are made by Sundararajan and Balino (1991). If depositors have rich information about banks (particularly that they are solvent), then runs should (theoretically) not take place.

At the time, South Africa was one of only a few G-20 nations that did not have a system of deposit insurance in place. There are very few modern banking episodes where deposit insurance is not present in some form (Martin et al., 2017). In this regard, the episode is not dissimilar to the bank failures in the United States during the 'National Banking Period,' the time between the passage of the National Banking Acts of 1863/4 and the creation of the United States Federal Reserve in 1913. There is a rich literature on this period, arguably due to the number of failures and the observed heterogeneity.[12] This literature shows that bank failures may be due to a number of factors, including common exposures (an exposure to a particular type of asset class, e.g. property, unsecured loans), a particular liability structure (e.g. reliance on short-term wholesale funding), or mismanagement (e.g. pursuing low margin business).

Finally, the episode takes place outside of a sovereign distress, in contrast to many of the banking episodes' experiences, particularly in other emerging markets and indeed some advanced economies (see, for example Kaminsky and Reinhart (1999), Reinhart and Rogoff (2013), Lane (2012) or Provopoulos (2014)).

3 Institutional setting

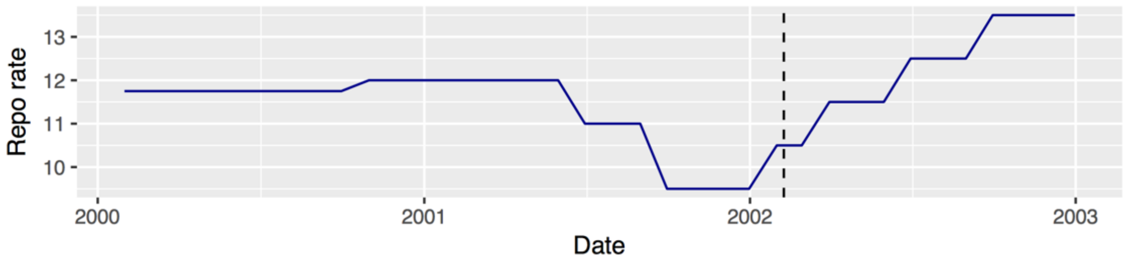
In the year leading up to the crisis, monetary conditions were relatively loose (see Figure 3). The overnight policy rate ('repo rate') had been reduced by 250 bps from 12 per cent to 9.5 per cent during 2001. On the back of the reduction in the policy rate, credit extension rose. Credit growth[13] averaged 6.9 per cent in 2000 and 8.6 per cent in 2001. The increase was most significant in personal loans, which expanded 27.4 per cent in 2000 and 26.7 per cent in 2001. Unifer and Saambou both had substantial exposure to this type of loan.

The reduction in the policy rate was a contributing factor towards a sharp depreciation in the exchange rate, although not the only reason.[14] During the course of 2001, the

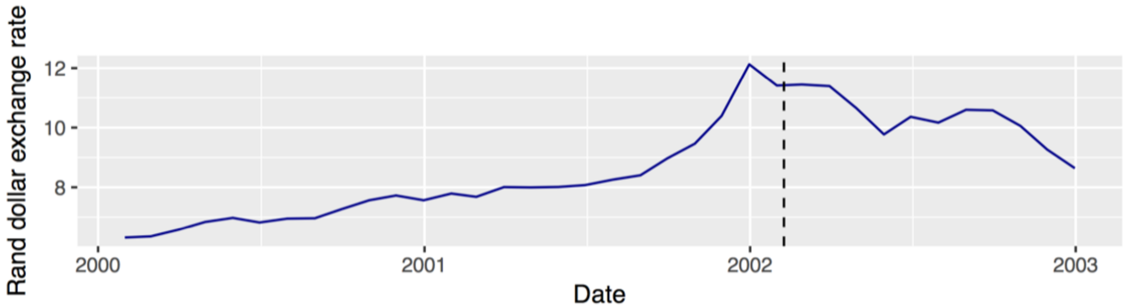
[12] See, for example, Friedman and Schwartz (1963), DeLong and Summers (1986), Calomiris and Gorton (1991),Calomiris and Mason (2003), Calomiris (2008), Gorton (2008), Gorton et al. (2014) and Jalil (2015)).

[13] Calculated as the monthly average of the year-on-year growth rate.

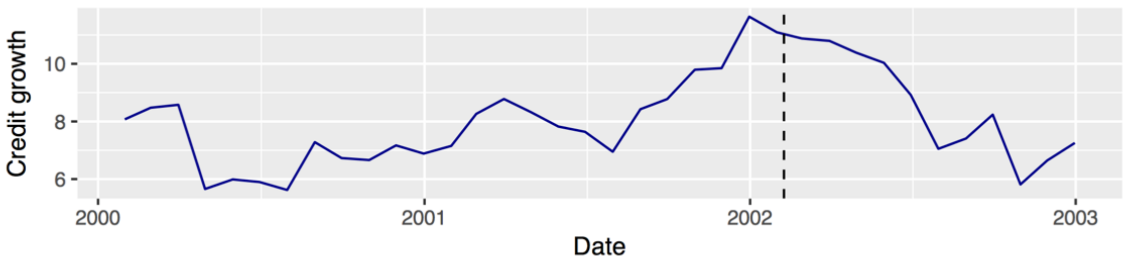
[14] A subsequent Commission of Enquiry could not pin-point a specific reason for the depreciation, but



(a) Shortly before the Saambou failure, the repo rate was increased by 100 bps. During the midst of the crisis, the repo rate was raised again.



(b) The exchange rate had depreciated rapidly during the course of 2001 reaching an all-time low by the end of the year.



(c) Credit extension had risen rapidly during the course of 2001.

Figure 3: Macroeconomic variables, 2000 – 2003

Overnight policy rate ('repo rate'), the exchange rate and private sector credit extension growth. The date of the Saambou failure is indicated by a dashed line.

Source: South African Reserve Bank, monthly data

rand/dollar exchange rate depreciated significantly, from R7.79 a US dollar in January 2001 to R12.13 a dollar in December, a depreciation of 55.6 per cent.

The number of registered banks increased from 35 in 1994 to 41 by 2000,[15] and the

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noted a number of contributing factors. These included (i) the reduction in the central bank policy rate; (ii) large foreign direct investment transactions; and (iii) the effective tightening of exchange-control requirements, which created a lack of liquidity in the market.

[15]Information obtained from the Annual Reports of the Registrar of Banks.

number of foreign-owned banks with local branches rose from 4 to 15.[16] The effect was to create a substantially more competitive banking environment.[17]

Against the backdrop of relatively loose monetary policy, and financial liberalisation, there was a rapid expansion of unsecured loans to vulnerable consumers. This was a concern to the authorities.[18] Lenders were guaranteed that payments would be honoured as they would be deducted prior to the employee even having his or her salary paid into their bank account. Arguably the loan was more secure than a secured loan, because secured loans could only be serviced from the remaining money. Despite this, they were charging interest rates as if the loan were unsecured. It was a very profitable, low-risk business.

Table 3: Growth in personal loans, selected periods

Period	%
Oct 1995 to Sept 2000 (Automatic deductions stopped)	16.9%
Sept 2000 to Feb 2002 (Saambou failed)	10.7%
Mar 2002 to Dec 2002	0.8%

4 Methodology

All South African banks experienced a similar institutional setting, but only some failed. The first research question considers why certain banks experienced a run and others not, while a second related question is why some failed immediately, and others later.

To illustrate – out of the ten smallest banks in the sample, only three experienced runs. At the time of the failure, these banks had similar-sized balance sheets, relatively similar capital adequacy levels and operated in a similar market. BOE, the largest and most significant bank that failed, was only marginally smaller than Investec, which was completely unaffected. This was despite Investec holding a significant indirect share of Saambou. Moreover, BOE had a diversified lending book and was not particularly exposed to unsecured lending. The deterioration in the external environment was common to all these banks, but only some appear to have been affected. *A priori*, it appears that there

[16] For a discussion of the financial liberalisation initiatives see Jordaan (1997), Jones (2003), Verhoef (2009) and Gilbert et al. (2009).

[17] See also Figure 1.

[18] The rise of microlending was one of the defining features of the post 1994 financial system (Porteous and Hazelhurst, 2004). In 1992, to support lending, exemptions to the Usury Act were granted. The effect was to remove the interest rate caps on short-term (less than 36 months) loans of less than R6 000. Microlending had been envisaged to be a way of supporting financing of small entrepreneurs. The experience was different – microlending expanded most strongly as a source of consumer credit. It created increasing distress, and government workers were particularly badly affected by the practice.

is a set of bank-specific characteristics that caused some banks to experience runs, but others not.

The research questions are approached using a set of techniques, including simple balance sheet scoring techniques, logistic regression, and survival analysis. In the results section, these approaches are compared for predictive power and suitability for real-time risk monitoring.

I consider each of these in more detail below. A summary of the usefulness of each approach is given in Table 4.

Table 4: Comparison of methodologies

Technique	**Estimation**	**Advantages**	**Disadvantages**
Balance sheet scoring	Probability of a failure in 24 months after t	Can be calculated *ex ante*. Computationally simple. Easily interpretable. Does not require accurate failure dating.	Assumes characteristics are time- invariant.
Logistic regression	Probability of a failure at any time after t_0	Relatively simple to estimate. Does not require accurate failure dating. Marginal effects are easily interpretable.	Estimated *ex post*. Assumes characteristics are time- invariant.
Ordered logistic regression	Probability of more than one outcome (growing, surviving or failing)	Exploits large number of observations.	Marginal effects difficult to compute. Requires failure dating.
Survival analysis	Probability of a failure at time t	Time to failure.	Requires accurate failure dating.
Machine learning k-NN	Probability of a failure	Priors about data not needed.	Requires substantial data. Does not test regressors. Requires accurate failure dating.

4.1 Balance sheet scoring

Regulators typically undertake balance sheet monitoring on a monthly basis, identifying the emergence of risks. The volume of data each bank submits to the regulator is significant, covering multiple aspects of the operations of a bank. A typical bank is required to submit 65,000 items of income statement, balance sheet and cash flow information on a monthly basis.[19]

Given the volume of data, and limited resources, simple balance sheet scoring methodologies are attractive. Moreover, the large literature and experience of using them in practical supervisory roles ensures that they are well suited for *ex ante* prediction of bank failure. This is in contrast to methodologies that rely on *ex post* analysis.

The most widely used technique is 'CAMELS', which is an acronym for the six main components of the regulatory coverage: Capital, Asset quality, Management, Earnings, Liabilities, and Sensitivity to market risk. The CAMELS regulatory approach is a well established and widely-used methodology for assessing bank risk (Bennett et al., 2015), Hwa et al. (2017), Kupiec et al. (2017), and has proven to be robust and reasonably comprehensive approach for evaluating bank risk. It is particularly appropriate for smaller banks, and forms the basis of the United States Federal Deposit Insurance Corporation (FDIC) approach to bank supervision (FDIC, 2018).

4.2 Logistic regression

Balance sheet scoring methodologies rely on an *ex ante* view of the relative importance of different factors in determining the probability of failure. A bank with weak liquidity, but otherwise strong scores in other areas, may still fail. Regression techniques provide an *ex post* approach to determining which factors have historically led to bank failures.

For the first set of analyses, I estimate the probability that a bank would experience a run, based on its own underlying characteristics using a simple regression of the form:

$$P(run_{i,j}|run_{S,j-1}) = \beta_0 + \beta_1 X_{i,j} \tag{1}$$

where $P(run_i|run_S)$ is the probability of a run on bank i at time j, conditional on a run having been experienced by the initial node (in this case Saambou) in the prior period, expressed as a function of a constant β_0 and a set of variables X_i at time j.

Logistic regression is well suited for this analysis, and is widely used in the literature. The dependent variable is binary (whether or not a run has occurred) and the independent variables are a set of characteristics of the banks in the sample. It is possible to estimate the marginal effect of a change in an independent variable on the probability of a run

[19] Estimated by using the number of data points required by the Regulations for Banks issued by the Minister of Finance.

occurring.[20] The model is estimated using maximum likelihood methods, and in R, the function used is `glm`.

In a linear regression, the parameter estimates are partial derivatives, dy/dx, or 'marginal effects,' i.e. they provide an estimate of the change in the dependent variable from a change in the independent variable. As logistic regressions are non-linear, the parameter estimates from cannot be interpreted in this way. To sensibly interpret the estimated coefficients, the marginal effects need to be calculated. For continuous variables, the marginal effects measure the instantaneous rate of change, i.e. the impact of a very small change on the dependent variable. The calculation provides a good approximation of the partial effect of impact of changes. In the results section below, both the odds ratio and the marginal effects are reported.

4.3 Ordered (multinomial) logistic regression

Despite the large outflows from affected banks, many banks saw significant inflows as depositors reallocated money between banks. Indeed, the annual average growth rate in deposits was was 14.8 per cent between beginning 2001 and 2002.

It appears some banks attracted depositors and others did not. It is possible to extend the logistic regression to an ordered multinomial regression. In this case, the dependent variable takes three states – grow, survive, and fail. These states are ordered: grow is regarded as superior to survive, which is superior to fail.

4.4 Survival models

A logistic regression provides a statistical technique to predict *that* a failure will occur, but does not predict *when* the failure will occur. There may be reason to believe that a set of independent variables may slow a failure (for example, liquidity) or speed it up (for example, other medical conditions).

Survival models (first introduced by Cox (1972)) propose a regression technique originally developed for use in medical research. It estimates the relationship between the survival time of patients and the underlying characteristics of those patients. The approach has also been extensively used for modelling other event studies with time as a factor. Examples of studies with bankruptcy include Shumway (2001), and for bank failures by Lane et al. (1986), Iyer et al. (2012), Cox et al. (2017), and Martin et al. (2017).

The Cox model specifies a 'hazard function', which introduces time as an element. The hazard $\lambda_i(t)$ for bank i at time t is given as:

$$\lambda_i(t) = \lambda_0(t)e^{X_i(t)\beta} \tag{2}$$

[20] A discussion of the approach is provided in Johnston and DiNardo (1997).

where λ_0 is the 'baseline hazard', which is time invariant and $_i(t)$ is a vector of variable, and β is the set of coefficients. The equation thus gives the effect on the baseline hazard of a set of coefficients multiplied by a set of variables. To interpret the hazard, one can calculate a 'hazard ratio', which gives the effect of a particular variable on the survival time. Assume, the hazard ratio with two subjects, i and j and fixed covariate vectors X_i and X_j, then

$$\frac{\lambda_i(t)}{\lambda_j(t)} = \frac{\lambda_0(t)e^{X_i\beta}}{\lambda_0(t)e^{X_j\beta}} = \frac{e^{X_i\beta}}{e^{X_j\beta}} \tag{3}$$

This allows the survival curve for one bank relative to another bank to be presented – for example, one could show how the survival probability of one bank with one set of characteristics relative to another.

This hazard ratio is constant over time, i.e. the hazard ratio is proportional, hence 'proportional hazard model.'

I use the `coxph` function in the `survival` package available in R to implement the Cox proportional hazards approach outlined above. The package calculates the hazard function and the set of β coefficients. The hazard ratio can be interpreted as follows. Where the $HR = 1$, there no effect, i.e. a unit change in the independent variable has a unit impact on the outcome; Where the $HR < 1$, then a change in that factor causes the likelihood of death to *decrease*; while if $HR > 1$, then that factor causes the likelihood of death to increase.

4.5 Random forest

The use of machine learning techniques for economic applications has expanded rapidly (Athey, 2017). Decision trees are simple and practical approaches to classifying data, and are popular classification approach in machine learning environments (Varian, 2014). These techniques have no theoretical underpinning and so provide an atheoretical approach to testing data hypotheses. Most significantly, machine learning techniques provide substantial opportunities for 'big data' (Varian, 2014), being well-suited for trawling large data sets looking for relationships. It is also well suited for algorithmic data analysis – fitting relationships in a structured way. For these reasons, the techniques are valuable during the data exploration phase of the question.

Here, I apply one type of methodology, the random forest decision tree. Decision trees may provide good predictions because of the use of a large number of explanatory variables (much as a large number of regressors will lead to a high unadjusted R^2). Varian (2014) notes the need to 'prune' the tree, which is simply a means of creating a cost for complexity (almost in the same way that the adjusted R^2 works).

The random forest model sequentially discriminates data into different categories. It is particularly useful for microeconomic questions, providing high out-of-sample fits, and is notably appropriate for highly non-linear data (Varian, 2014). A drawback is that it lacks simple summaries of relationships.

The performance of simple decision trees can be enhanced by expanding the 'tree' to a 'forest', that is, by using multiple trees Varian (2014). The multiple trees are created using bootstrap aggregating of random samples of observations. At each node (decision point, or 'leaf'), a random sample of predictors is chosen. This process is repeated multiple times. The final classification is determined by using a 'majority vote', that is by identifying which tree performed best on an aggregated basis.

5 Data

The data set contains monthly data on 217 individual *balance sheet* items for the full sample of 47 banks which had banking licences at the time of the Saambou curatorship, and for which there is sufficient data. Data is collected from January 2001 to December 2002, giving information on the 13 months prior to the failure and 11 months after. There are 244,776 data points.

The data is constructed from publicly-available detailed balance sheet data from the Banking Supervision Department of the South African Reserve Bank.[21]

5.1 Data pre-processing

From this information, a number of financial ratios and balance sheet items are constructed. These include summary balance sheet items.

There are data for 29 different asset types. These are aggregated into high-level categories – (i) Inter-bank assets; (ii) Resale and installment loans; (iii) Mortgages; (iv) Credit card loans; (v) Loans to companies (non-financial and financial); (vi) Other loans (mainly personal loans to individuals); (vii) Other investments and assets (mainly investments in financial intruments; and (viii) specific provisions.

There is information on twenty liability categories. These are aggregated and summarised into nine main categories: (i) Intergroup; (ii) Interbank; (iii) Public liabilities; (iv) Financial; (v) Non-financial; (vi) Individuals; (vii) Non-profits; (viii) Non-residents; and (ix) Other.

For each liability, tenor is also available in three buckets: short term, medium term and long term. This allows a further set of ratios to be constructed for duration.

This is complemented with historical performance data, including historic liability growth, retail deposit growth, and retail lending growth. Additional information, including

[21] Although confidential bank specific information provided by each bank was considered, for replicability and confidentiality reasons, this data was not included.

estimates of market share (by product line), are also calculated.

Finally, there is high-level information available on capital. From this information, a number of ratios are calculated. These include: equity-to-liabilities, equity-to-unweighted assets, equity-to-risk weighted assets, and a solvency ratio. The solvency ratio is defined as asset minus liabilities as a percentage of assets.

The data set is summarised in the Appendix.

5.2 Date of failure

For estimation purposes, it is important to define a '*bank failure*' and date it. There are two possible approaches. In the first approach, 'failed banks' can be designated as those that are either placed into curatorship or lose their licences (either voluntarily or because their financial positions have deteriorated significantly). The disadvantage of this approach is that the date of the failure may be too late – typically a licence is only withdrawn at the end of a depositor run. A second disadvantage is that it excludes banks which are rescued. Indeed, during the banking episode, BoE remained technically intact. The run took place in March 2002, but the licence was only withdrawn in early 2003 when the merger with Nedbank was finalised.

In the second approach, failed banks could be determined statistically – for example, banks that experience a run of more than 50 per cent of their deposits over the two-year period are deemed to have 'failed.' This approach side-steps some of the disadvantages above, but has its own disadvantages. Firstly, it is difficult to date the 'failure.' Is it at the end of the run, during the run, or when the run begins? For the banks in the 'second wave,' there is evidence of a slow run. Even banks in the 'first wave' had seen a slow run prior to Saambou curatorship. Secondly, the threshold of 50 per cent is arbitrary. Some banks lost their licences after a run of 20 per cent of their liabilities. Other banks lost all deposits. One international bank saw a plunge in its deposit base during the course of the episode, and managed to restore confidence to the extent that deposits returned.

For these reasons, for the purposes of this paper, I follow a hybrid of the two approaches, supplemented with publically-available information. I review each of the 47 banks in the sample, and match their licence information to the behaviour of their liabilities. Only failures in the 12 months following the Saambou failure are considered (the first and second waves), on the basis that it is the short-term contagion we are interested in. Moreover, evidence is sought that failed banks saw large outflows from the date of the Saambou event, i.e. experienced sustained runs. The dates are provided in Table 5.

This provides us with a set of 12 banks which 'fail,' and 35 banks which 'survive.' As noted above, in total 22 banks left the system, i.e. 10 additional banks deregistered as part of the consolidation. However, using the methodology here, these are not captured

Table 5: Dating of failures

Bank	Estimated failure	Cancellation / curatorship
International Bank	30-Sep-01	30-Apr-02
Corpcapital	31-Oct-01	29-Nov-02
TA Bank of SA	31-Dec-01	05-Apr-02
Saambou	15-Jan-02	09-Feb-02
Brait	31-Jan-02	30-Sep-02
PSG Investment	31-Jan-02	31-Oct-02
BOE Bank	31-Jan-02	21-Feb-03
Cadiz	15-Apr-02	15-Apr-02
FirstCorp	17-Apr-02	17-Apr-02
Old Mutual Bank	31-Aug-02	17-Dec-02
Merrill Lynch	15-Sep-02	05-Apr-02
Securities Investment	30-Sep-02	18-Feb-03

This table estimates the date that runs began on the twelve affected banks.
See text for an explanation of the methodology.

as failures – they are part of a third wave of consolidation which is considered separately in a later section.

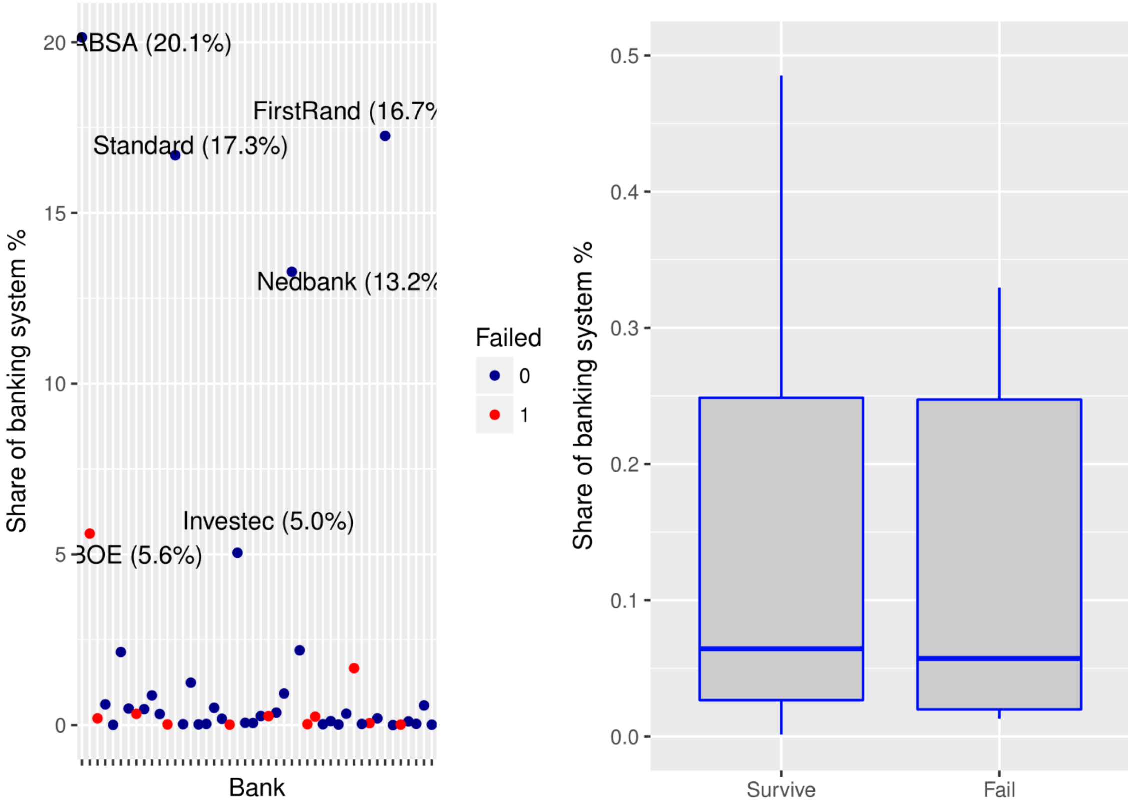
6 Results

6.1 Did size and interconnectedness matter?

The extensive data set allows for some preliminary analysis. One hypothesis is that only small banks failed, i.e. that this was a true 'small bank crisis,' which led to the failure of all small banks. From the data analysis, the answer to this appears more nuanced. The four large banks, defined as those with market share of more than 12.5 per cent, did indeed survive. However, out of the two mid-tier banks (banks with a market share of between 2.5 per cent and 12.5 per cent), one failed (BOE) and one survived (Investec). As seen in Figure 4, the group of 41 small banks (those with a market share of less than 2.5 per cent), 11 failed and 30 survived.

A second simple hypothesis is that the banks were highly connected. The data allows some testing of interconnectedness between banks, and how this interconnectedness changed during the course of the crisis. The authorities intervened with BOE to stabilise its liquidity situation, and this was reflected in a sharp increase in interbank liabilities. For this reason, I exclude BOE from the analysis and focus on the banks that failed, also conducting some preliminary tests for interconnectedness in Figure 5.[22]

[22]This only provides aggregate interbank exposures. We also analyse the financial statements of both



(a) All very large banks survived (those with a market share of over 12.5% of the system. However, amongst the small banks, failures appear equally distributed.

(b) Out of the sub-set out banks with a market share of less than 2.5 per cent, box-plots confirm that the size of surviving and failing banks was on average the same. ANOVA tests confirm that small banks were not more likely to fail.

Figure 4: Did the size of the bank matter?

6.2 CAMELS analysis

In terms of a CAMELS analysis, three of the components in the CAMELS analysis put forward in Figure 6 are notable: capital, liquidity and market risk.

Banks that failed had substantially more capital than those that survived (Panel 1 in Figure 6). Moreover, they had better solvency ratios, defined as the difference between assets and liabilities as a percentage of assets (Panel 2). As the failing banks were better capitalised and more solvent than surviving banks, solvency clearly was not the concern. This is a consistent finding across all methodologies.

Failing banks also had shorter-term, wholesale funding (Panels 7 and 8). The types

Saambou and the affected banks, and there is no evidence that there were any interbank linkages between Saambou and the banks that failed.

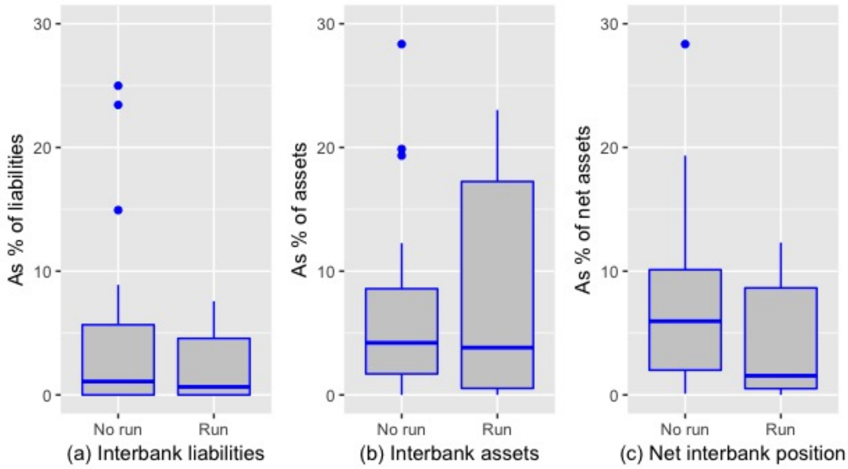


Figure 5: Box-and-whisker plots, interconnectedness.
I test the hypothesis that more interconnected banks were more likely to fail following the Saambou failure. There is no evidence with banks with large exposures to other banks were more likely to experience runs. ANOVA tests confirm these results. BOE is excluded as it had a large interbank position due to the liquidity guarantee.

of liabilities differed significantly: failures had a higher proportion of short-term liabilities and a higher proportion of wholesale liabilities. This suggests that it was not a 'retail deposit' run, but rather a run by short-term wholesale funders.

This is borne out by Panel 10, where it is notable that the failing banks had a smaller proportion of funding from retail depositors than surviving banks. While the Saambou run was due to relatively sophisticated retail depositors, it is clear that the run on other banks was due to a wholesale run. South Africa did not have a deposit insurance scheme at the time of the failure. As it was not a depositor run, deposit insurance would not have staunched the outflow.[23]

The third difference between surviving and failing banks is sensitivity to market risk. This is measured by considering the percentage of the balance sheet invested in financial instruments (defined as investments including trading portfolio assets). Failing banks had a notably higher exposure to these trading assets, suggesting they were particularly affected by movements in share prices, possibly as part of the fall in bank share prices that occurred over the period between Unibank and BOE failing.

The analysis also shows that the failing and surviving banks did not differ substantially in terms of asset quality and earnings (Figure 6 presents three types). Non-performing loans as a percentage of total loans and advances were not different between surviving

[23]The traditional argument for deposit insurance (see Diamond and Dybvig (1983)) is that it avoids a panic depositor run, as bank deposits are safe. In this case, the deposit insurance scheme would have had to apply to non-retail deposits too.

and failing banks. Neither the return on assets nor the types of assets differed – both surviving and failing banks have approximately similar exposures to unsecured assets and to mortgages.

6.3 Why did some banks fail? Logit regression results

The preliminary indication from the CAMELS analysis is that that certain banks failed because they were more fragile than others – that is, they had weak balance sheets. The results of a set of logistic regressions, presented in Table 6, bear out the evidence that balance sheet structure influenced the probability of failure. I test a variety of specifications, to ensure robustness of results.

Across all specifications, increased short-term funding from non-bank financial institutions ('short-term wholesale funding') is associated with an increased probability of failure. This is consistent with a view that increased short-term wholesale funding increases bank funding risk, a finding also demonstrated by Huang and Ratnovski (2011) and De Bruyckere et al. (2013) amongst others.

There is a persistently statistically significant coefficient on deposit growth, and the sign is negative. I test for different specifications. In specification 1, I test for the total growth of liabilties in the year prior to the failure. The coefficient is -0.042, with a standard error of 0.017. In an alternative specification, presented as specification 2 of Table 6, I use the growth in deposits only (i.e. excluding non-deposit liabilities). In this specification, the coefficient of interest is smaller, but still negative (-0.018, with a standard error of 0.009).

The evidence in Figure 2 also suggests this, and it is notable that on aggregate, the banks that experienced runs in 2002 had already started seeing outflows. This suggests that for whatever reason, there were already indications from depositors about concerns with these banks. This does highlight that these banks may already have been perceived to be weak, and that the Saambou curatorship (and the Unifer/Unibank announcement) confirmed suspicions about small banks with large exposure to personal loans.

Specification (4) adds the role of exposure to financial instruments. Banks with large exposures to financial instruments are found to be more likely to fail. A number of different types of asset exposures were considered, but only 'Other Assets' was found to to be statistically significant ('Other assets' measures the extent of investments in financial instruments, financial assets and derivatives. It provides a market risk measure). A simple 'sanity check' – analysing the distribution of assets between failed banks and non-failed banks shows that there is no evidence of common exposures, i.e. the banks did not have similar loan portfolios.

Specification (5) tests the role of capital. A number of measures are used, and the

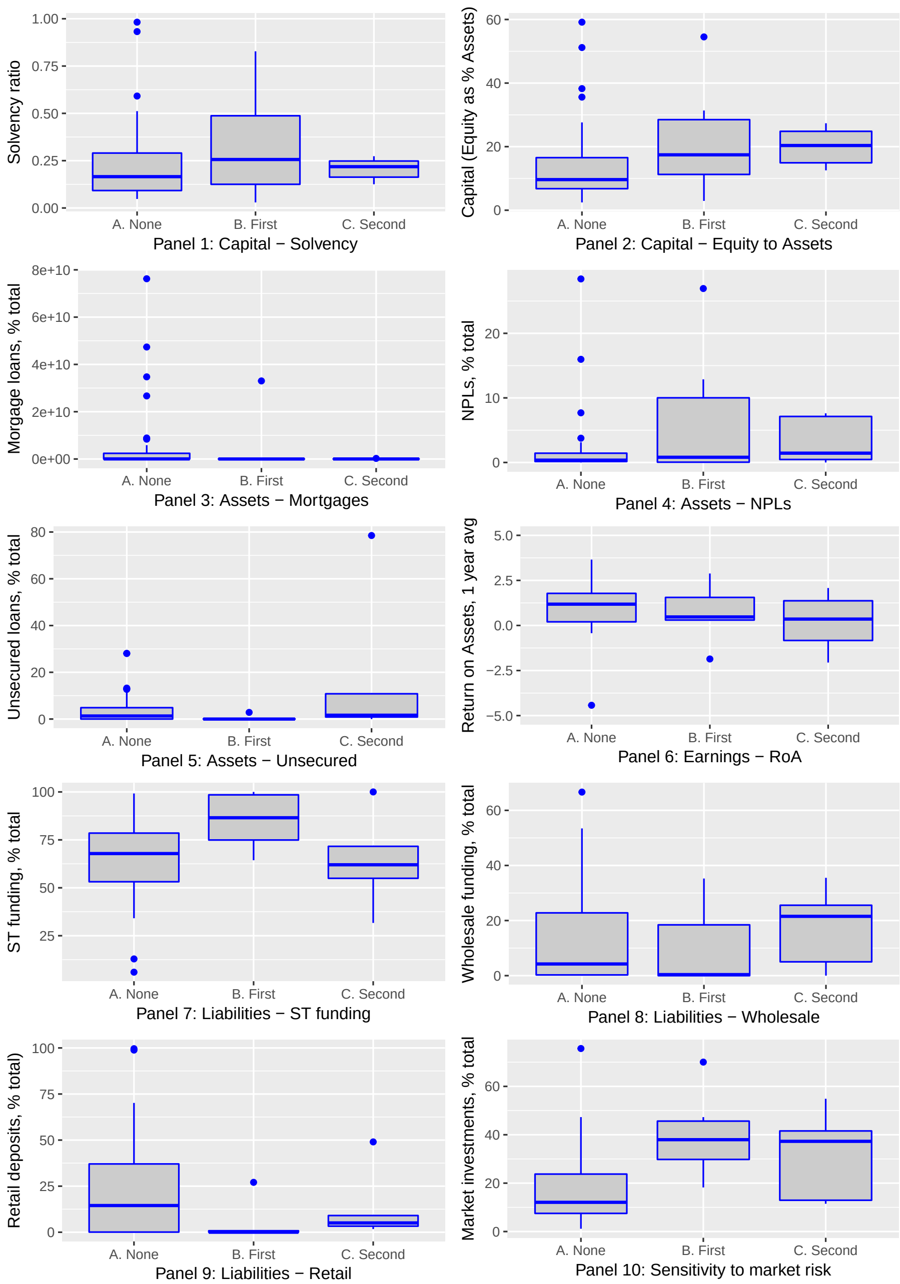


Figure 6: CAMELS analysis

Surviving and failing banks are compared using the CAMELS methodology. I find a statistical difference between failing and surviving banks in the following areas: (i) Capital, with failing banks having higher levels of capital, (ii) Liabilities, with failing banks having higher levels of short-term and wholesale funding from non-bank financial institutions; and (iii) Sensitivity to market risk, with failing banks being more exposed to financial instruments.

role of simple unweighted assets to liabilities is reported. It is statistically significant and positive, in line with the results obtained in Figure 6. Interestingly, it appears that the coefficient on financial instruments is no longer statistically positive. However, other measures of capital (not reported here) show that financial instruments remain statistically significant. For example, when using the equity-to-debt ratio as a measure of capital, the share of financial instruments is still significant. As noted below, the predictive power of equation 5 is best, suggesting that thus specification captures the data best.

Table 6: Why did some banks fail? Logit regression results

	Dependent variable:					
	Probability of failure					
	(1)	(2)	(3)	(4)	(5)	(6)
Fin. sector liab (share)	0.096^{**}	0.074^{**}	0.060^{**}	0.108^{**}	0.121^{**}	0.130^{**}
	(0.040)	(0.034)	(0.030)	(0.046)	(0.050)	(0.058)
Liability growth	-0.042^{**}		-0.031^{**}	-0.043^{**}	-0.049^{***}	-0.048^{*}
	(0.017)		(0.013)	(0.019)	(0.018)	(0.026)
Deposit growth		-0.017^{*}				
		(0.009)				
ST liabilities (share)	0.113^{**}	0.067^{**}	0.051^{*}	0.118^{*}	0.104^{**}	0.100
	(0.051)	(0.032)	(0.027)	(0.062)	(0.050)	(0.063)
Other assets (share)				0.049^{*}		0.045
				(0.029)		(0.037)
Equity to Liabilites					0.110^{**}	0.101^{*}
					(0.056)	(0.056)
NPL ratio						0.007
						(0.111)
Constant	-10.571^{**}	-7.085^{**}	-5.169^{**}	-12.560^{**}	-12.513^{***}	-13.564^{**}
	(4.380)	(2.797)	(2.146)	(5.537)	(4.763)	(5.651)
Observations	45	45	46	45	45	45
Log Likelihood	−12.658	−16.442	−17.299	−10.946	−9.493	−8.380
Akaike Inf. Crit.	33.315	40.885	42.599	31.891	28.986	30.759

Note: *p<0.1; **p<0.05; ***p<0.01

This table presents the results of logistic regressions. The dependent variable takes the value of 1 if a bank 'fails' in the *twelve-month period* following the Saambou failure. The dependent variables take their values at the point that Saambou went into curatorship. Cadiz Bank is dropped due to poor data quality.

6.3.1 Predictive power

The predictive power of the model is presented in in three ways. First, the predicted probabilities for the year prior to the Saambou curatorship are presented in Figure 7. I present the average predicted probability for all banks and for the group of failed banks. It is notable that banks were weak *ex ante*. The Saambou failure appears to have triggered the failure of banks that were already weak due to fragile balance sheets (particularly an over reliance on short-term wholesale funding).

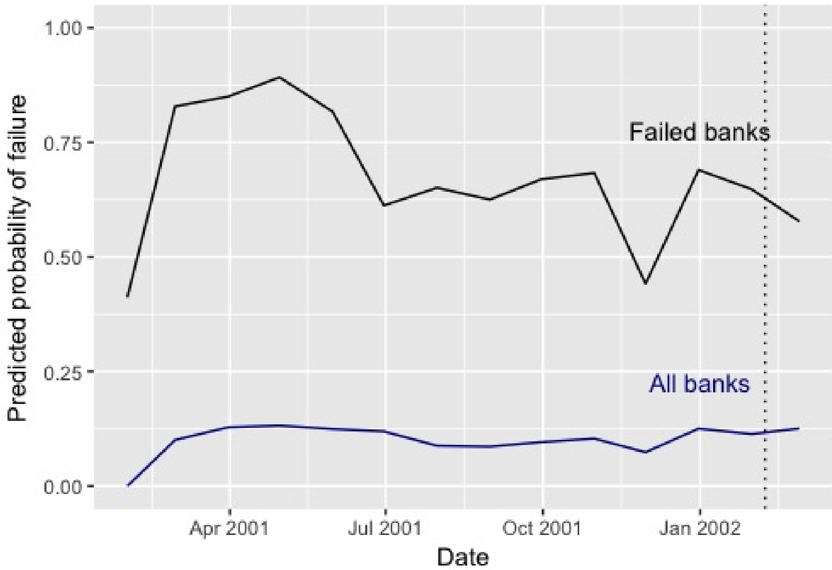


Figure 7: Probability of failure

The figure presents the probability of failure for failed banks and all banks. The date of the Saambou curatorship is indicated with a dashed line.

The second way to test for do this test how accurate the model is in predicting individual failures. Four of the specifications in Table 6 are tested: specification 1, 2, 4 and 5. I exclude specification 3 as that included Saambou; and specification 6 as other statistical tests suggest the parameters are not significant. The predictive power of the model is presented in Table 7. Specification 5 emerges as the best from a fit perspective. 33 banks are classified correctly as 'Survive.' Two surviving banks are classified as 'Fail.' Two banks that failed are predicted to survive, but 8 failed banks are correctly predicted to fail.[24]

[24]Recall that twelve banks failed. The model only contains ten banks as Saambou is excluded, and Cadiz bank did not have sufficient data for the analysis.

6.3.2 Marginal effects

As discussed in section 4.2, the coefficients from logit models are not immediately interpretable, in contrast to the coefficients from linear regression. Marginal effects need to be calculated to obtain an estimate of the impact of a unit change in the dependent variable on the probability of the event. These are presented in

I present the marginal effects in three ways: as joint marginal effects, average marginal effects and as conditional expected values. Figure 8 presents the *joint marginal effects*, i.e. the interaction of two variables at the same time.

Panel a of Figure 9 presents the *average marginal effect*. Though marginal effects are non-linear an average effect can nevertheless be estimated by considering a unit change at mean of the dependent variable. Panels b and d of Figure 9 present the *conditional expected values* of the probability of failure given a set of different values for financial liabilities, as a proportion of total liabilities and as a ratio of short-term liabilities to long-term liabilities, respectively, show a strong positive relationship with the probability of failure. Panel c highlights the results indicated above - which is that the probability of a run is inversely related to deposit growth. Put another way – negative deposit growth in the year prior to the failure increases the probability of a run. This suggests failing banks were already experiencing outflows.

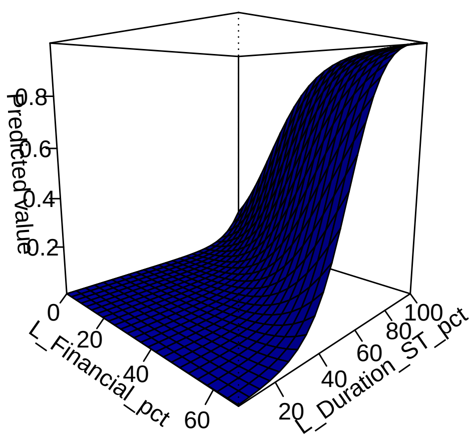


Figure 8: Joint marginal effects

The probability of failure shown as a result of the joint effects of an increase in both financial and short-term liabilities as a percentage of total. The model predicts that banks with high percentages of short-term and financial liabilities were very likely to fail.

Table 7: Goodness of fit estimates: logistic regression

Eq. 1				**Eq. 4**			
	P(Survive)	P(Fail)			P(Survive)	P(Fail)	
Survive	33	2	35	Survive	33	2	35
Fail	4	6	10	Fail	3	7	10
	37	8			36	9	

Eq. 2				**Eq. 5**			
	P(Survive)	P(Fail)			P(Survive)	P(Fail)	
Survive	32	3	35	Survive	33	2	35
Fail	6	4	10	Fail	2	8	10
	38	7			35	10	

Goodness of fit statistics	(1)	(2)	(3)	(4)	(5)	(6)
McFaddenR^2	0.47	0.31	0.32	0.54	0.60	0.65
R^2 ML	0.39	0.28	0.29	0.44	0.47	0.50
R^2 CU	0.60	0.43	0.44	0.67	0.72	0.76
Hosmer-Lemeshow C stat (p-value)	0.39	0.85	0.13	0.62	0.54	0.62
Hosmer-Lemeshow H stat (p-value)	0.29	0.29	0.76	0.85	0.74	0.85

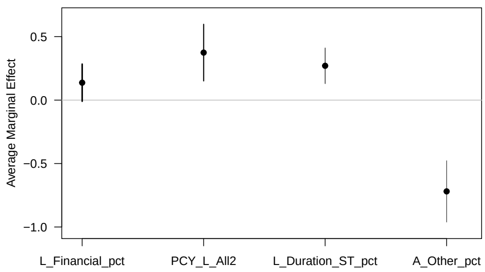
Note:
This table presents a simple goodness of fit measure ('confusion matrix') for the logistic regressions in Table 6. The upper panel presents the number of predicted fails against the actual fails. This allows for the identification of Type 1 errors (false positive) and Type 2 errors (false negatives). The lower panel presents different pseudo-R^2 statistics for logistic regressions. Cadiz Bank was dropped due to data quality.

6.4 Why did some banks fail later than others?

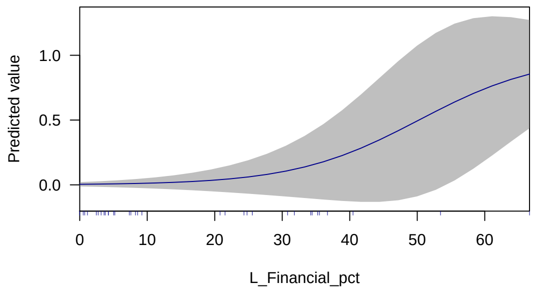
The Cox proportional hazard model, detailed in the methodology section, incorporates the time to failure in estimation technique. In Table 8, I present the results of the Cox proportional hazard regressions.

In specification (1), I test the impact of increased wholesale funding, deposit growth, short-term funding, other assets and non-performing loans on the probability of failure at time t. It is immediately apparent that the same variables are statistically significant for both the logistic and Cox survivor methodologies. In particular, wholesale funding is significant and positive, indicating the probability of failure is increased (or probability of survival reduced).

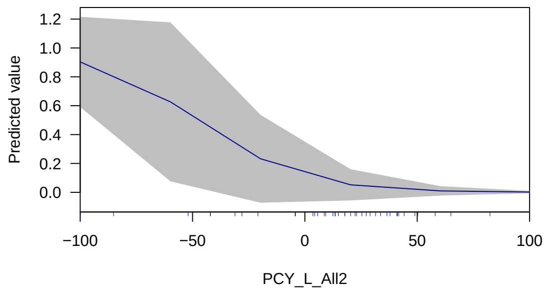
Historical liability growth is similarly statistically signficant and negative, underscoring the finding that banks that were already experiencing outflows were more likely to fail, and that the failure of Saambou may only have accelerated the run, rather than precipitated it. Moreover, exposure to financial instruments is also statistically significant and positive, similarly to the logistic regression findings.



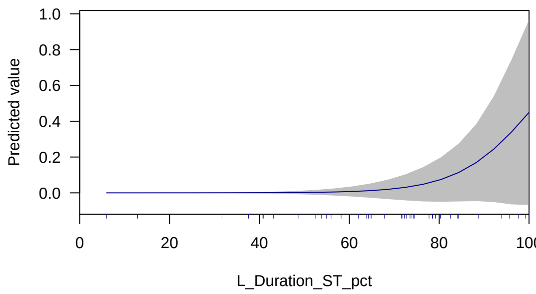
(a) Computed average marginal effects and standard error bands, derived from specification 4



(b) The probability of a run is an increasing function of the proportion of financial liabilities. Here we present the probability of failure as the conditional expected value given a locus of financial liabilities as a percentage of total liabilities. The conditional expected value is derived from the marginal effects model.



(c) The probability of a run is inversely related to deposit growth in the year prior to the Saambou failure.



(d) The probability of a run is an increasing function of the ratio of short-term liabilities to long-term liabilities.

Figure 9: Marginal effects

Although wholesale funding is statistically significant for the Cox regression results, short-term funding is not. The Cox regressions highlight that the structure of funding appears to create the difference in the time-to-failure. Both first and second wave banks were at risk of failure, with evidence that weak banks failed sooner if they had short-term funding. This is consistent with evidence from other countries; banks with short-term liabilties are more fragile when faced with an exogenous shock (Huang and Ratnovski, 2011).

The most notable difference between the logit regression results and the Cox results is the role of non-performing loans. There is also an increased likelihood of failure for banks with higher non-performing loans. I test for any correlation between non-performing loans and other variables, in case there is multicollinearity. In particular, the correlation is low between unweighted capital adequacy and non-performing loans (0.134), between exposure to financial instruments and non-performing loans (-.043), and between exposure fo financial instruments and unweighted equity (0.191).

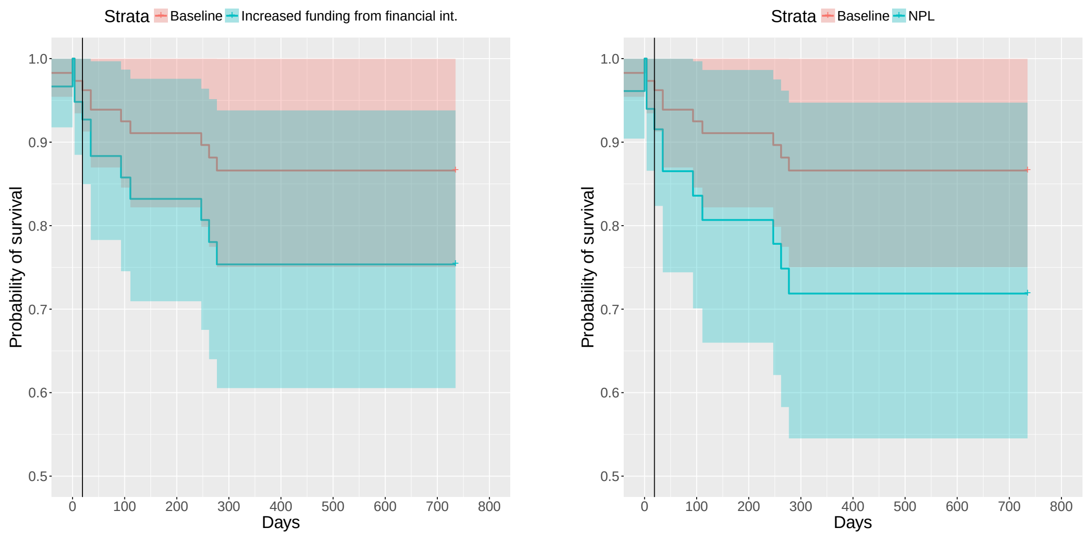
Table 8: How did time influence failure? Cox survivor analysis results

	Dependent variable:		
	Days_to_run2		
	(1)	(2)	(3)
Fin. sector liab (share)	0.097**	0.052**	0.105***
	(0.040)	(0.024)	(0.039)
Deposit growth	−0.017*		−0.017*
	(0.010)		(0.010)
ST liabilities (share)	0.022		
	(0.018)		
Other assets (share)	0.062**	0.054***	0.073***
	(0.029)	(0.018)	(0.027)
Equity to Liabilites	0.066**	0.039**	0.058**
	(0.027)	(0.019)	(0.024)
NPL ratio	0.140*	0.118**	0.153**
	(0.072)	(0.053)	(0.072)
Observations	45	46	45
R^2	0.453	0.294	0.431
Max. Possible R^2	0.807	0.830	0.807
Log Likelihood	−23.416	−32.819	−24.302
Wald Test	11.140* (df = 6)	11.630** (df = 4)	9.990* (df = 5)
LR Test	27.144*** (df = 6)	15.995*** (df = 4)	25.371*** (df = 5)
Score (Logrank) Test	23.301*** (df = 6)	16.916*** (df = 4)	21.902*** (df = 5)
Note:			*p<0.1; **p<0.05; ***p<0.01

This table presents the results of Cox survivor analysis. Failures are dated according to a hybrid approach discussed in the text. The dependent variables take their values at the point that Saambou went into curatorship. Cadiz Bank is dropped due to poor data quality.

6.4.1 Interpreting the results

Cox survivor analysis can be interpreted through survivor curves. These graphically present how estimated survival depends upon the value of a covariate of interest. Survivor curves plot the probability of survival of the mean bank, i.e. a bank with characteristics at the mean. A plot of the survival of a hypothetical alternate bank, with different characteristics can then be compared to that of the mean bank. Figure 10 shows the survival probability for a bank with increased wholesale funding and increased non-performing loans. The dramatic deterioration in survival probability is evident.



(a) Dynamic survival probability for a median bank: baseline and with a one standard deviation increase in wholesale funding

(b) Dynamic survival probability for a median bank: baseline and with a a one standard deviation increase in non-performing loans

Figure 10: Survival plots

6.5 Why did some banks grow? Ordered logit

For the purposes of the next part of the analysis, banks are classified into three sub-populations: $GROW$ refers to banks which increased their deposits by more than 15 per cent in the two years following the Saambou curatorship. $SURVIVE$ are banks that saw relatively stable position, defined as between a 0 per cent and a rise of 15 per cent. Finally, $FAIL$ are banks that failed, as per the definition above.

In Table 9, the results of ordered logits are given. The coefficients are of similar signs, albeit of different sizes. It is notable that both the percentage of short-term funding and the percentage of non-performing loans are not found to be statistically significant for the purposes of identifying which banks *survived*. Put another way, these two variables do not explain the survival of banks relative to other banks.

Table 9: Why did some banks fail? Ordered logit regression results

	Dependent variable:		
	Ordered logit specification		
	(1)	(2)	(3)
Fin. sector liab (share)	0.055**	0.056**	0.055**
	(0.024)	(0.024)	(0.024)
Liability growth	−0.022***	−0.023***	−0.022**
	(0.009)	(0.009)	(0.009)
Deposit growth		0.007	
		(0.015)	
ST liabilities (share)			−0.0003
			(0.053)
NPL ratio	0.050**	0.050**	0.050**
	(0.024)	(0.024)	(0.024)
Observations	45	45	45

Note: *p<0.1; **p<0.05; ***p<0.01

This table presents the results of ordered logistic regressions. The dependent variable takes the value of 2 if a bank 'fails' in the *twelve-month period* following the Saambou failure, 1 if it 'survives' (deposits remain stable or grow) and 0 if it grows by more than 15 per cent.. The dependent variables take their values at the point that Saambou went into curatorship. Cadiz Bank is dropped due to poor data quality.

6.6 Machine learning: Random forest

Figure 11 presents the decision tree graphically. A decision of 1 is a bank failure. At the first decision node, the question is 'Is short-term duration less than 100?' If *no*, then the right-hand branch is followed. Here, the algorithm shifts to the next decision node. The next question is 'Is the solvency ratio larger than or equal to 0.81?' If *yes*, then the left-hand node is followed, and the answer is 0, i.e. no failure. If *no*, then the right-hand branch is followed, and the answer is 1, i.e. a failure.

This may be interpreted as saying that banks short term funding ratio of 100 per cent will fail if their solvency ratios are less than 81 per cent. If *yes*, then further questions are asked about the asset quality of the bank, with final decisions of either 'fail' or 'survive.'

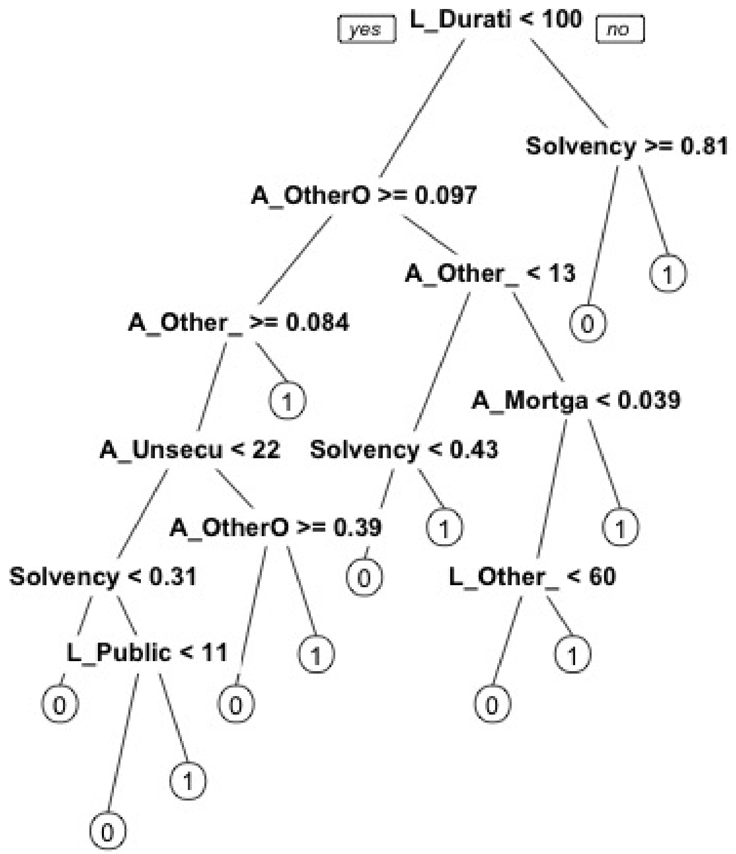


Figure 11: Decision tree

The random forest approach has the advantage of ordering variables in terms of importance, similar in some ways to principal components analysis. In Figure 12, I generate a variable importance plot from the random forest model above.

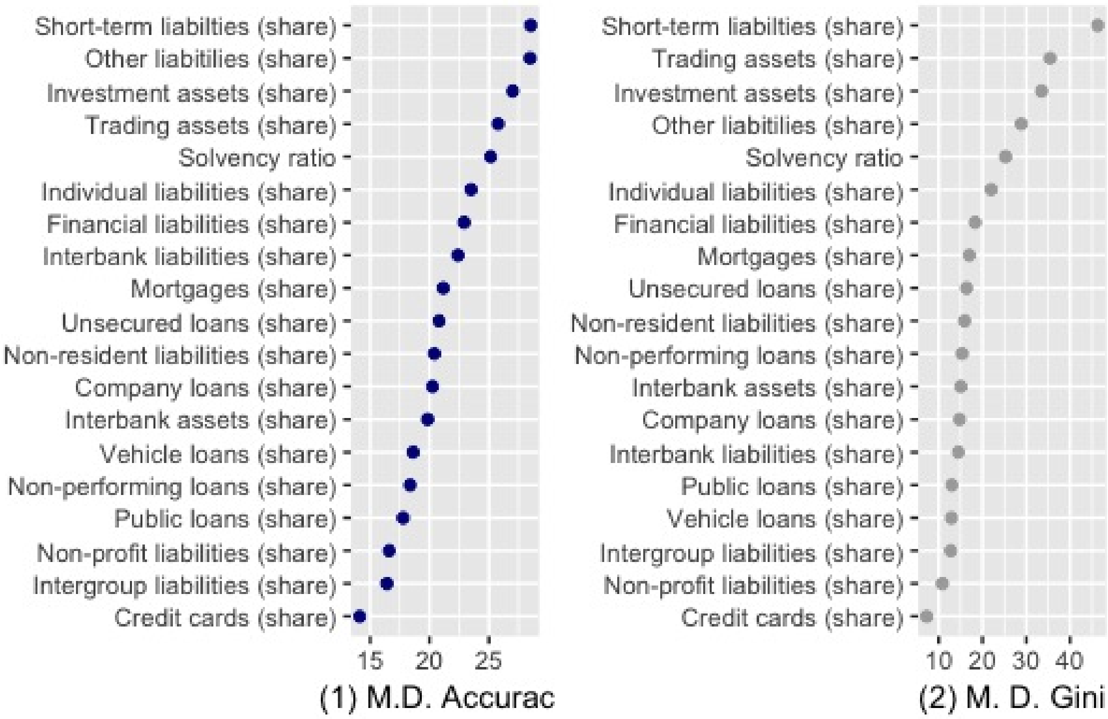


Figure 12: Variable importance plot

This presents the variables used in the random forest model in order of relative importance to the decision. Two tests are used – Mean Decrease Accuracy and Mean Decrease Gini. The former measures the impact of excluding a variable on the accuracy of the model. The latter is a related measure that technically measures the impact of the variable on the homogeneity of the nodes and leaves. The most important variable is short-term liabilities.

It shows a somewhay different outcome from the analysis using traditional econometric techniques. The percentage of short-term funding is still the dominant driver of the results. However, the proportion of 'Other Assets' is the second most important determinant of failure. (Recall that 'Other Assets' are financial instruments. Banks with these assets are more typically investment banks). In the CAMELS analysis, this was also noted (see Panel 10 of Figure 6, and the discussion in section 6.2). In the logistic regression, specification 4, this variable was statistically significant, but only at the 10 per cent level. Moreover, the odds ratio was smaller than the financial sector liabilities odds ratio.

This shows the power of alternative machine-learning techniques to bring out data features not necessarily captured by traditional econometrics, a point also made by Varian (2014).

6.7 Can these results predict other failures?

The results in this study are particular to the 2002/3 period. The model performed relatively well at predicting in-sample failures (recall Figure 7 and Table 7). However, it is a worthwhile experiment to see if the results can accurately predict others bank failures, particularly the 2014 failure of African Bank (discussed in Havemann (2019)) and the 2018 failure of VBS Mutual Bank.

Data from African Bank and VBS Mutual Bank is placed into the specification 4 of the logistic regressions reported above. I use the data from their balance sheet in the year prior to failure to generate the predicted probability of failure. In the case of African Bank, it is a years' worth of data starting in August 2013; and in VBS Mutual Bank, a year of data from February 2017. The results are plotted in Figure 13. It shows that the model is quite accurate at predicting even completely out of sample failures (both failures were characterised by banks with high levels of wholesale and short-term funding, which deteriorated as the failure neared).

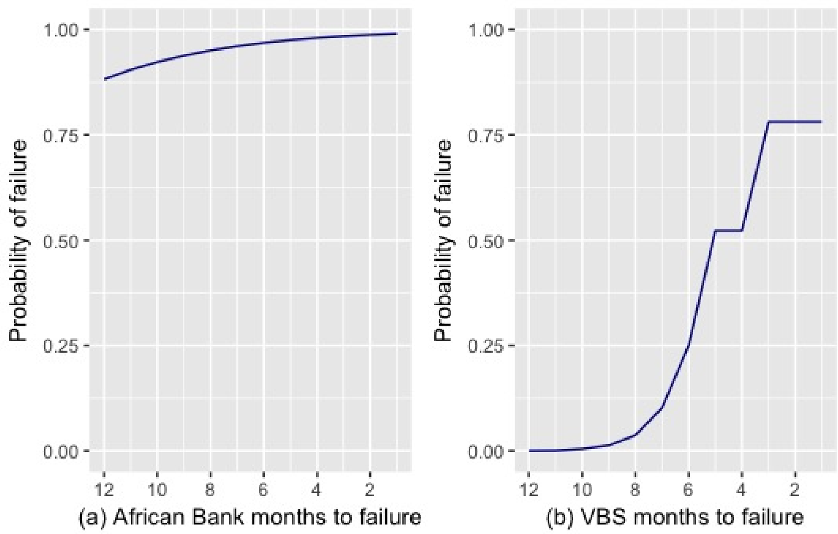


Figure 13: Predicted failure probabilities

The balance sheet data for African Bank (Panel a) and VBS Mutual Bank (Panel b) for the twelve months ahead of the failure is placed into the model.

6.8 Long-run effect of the Saambou collapse

The consolidation substantially increased concentration in the banking system. Before the crisis, BOE had a market share of 13.1 per cent of the mortgage market, and Saambou had a 3.3 per cent share. The crisis reduced the competitiveness of the mortgage market. Reviewing the data highlights another feature of the episode. In a closed system (i.e. a system with a sovereign currency and currency convertibility rules such as South Africa), liquidity cannot move outside of the system. This partially due to currency convertibility rules. Only Authorised Dealers (ADs) can convert rand into other currencies. These ADs must, in turn, be registered South African banks. The effect is that rand liquidity circulates between ADs. This is quite different from a run on Greek banks, for example. Any bank in the euro area can accept Euros. Thus the liquidity of the euro can move from Greece to Germany. Conversely, in a closed system, a run on one bank must reflect as an inflow into another, or alternatively as an increase in notes and coins.[25]

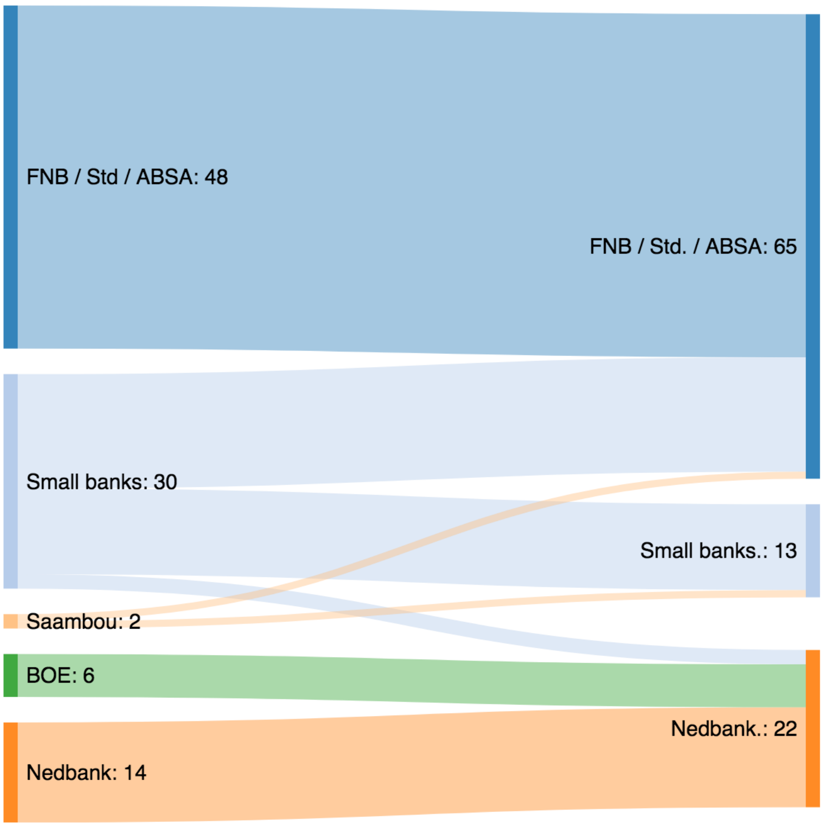


Figure 14: Market share: Before and after consolidation

Market share of 'other banks' fell from 22 per cent to 12 per cent. BOE was wholly subsumed into Nedbank, and Saambou was split between FNB (Homeloans) and African Bank (personal loans).

The experience in South Africa was indeed that liability holders reallocated their deposits and there was a a discernible 'flight to quality'. Simply put, a set of banks experienced substantial inflows. While more than four banks experienced inflows, the majority

[25]The increase in notes and coins is a feature of episodes in other countries, particularly in the National Bank Period and failures in less developed countries

of flows went to four. These banks are now known as the 'Big Four' because of their dominance, but prior to the episode they were not as significant. In January 2002, prior to the curatorship, these four accounted for 62.4 per cent of assets. By January 2003, they accounted for 88.4 per cent of assets.

The most notable 'winner' from the episode was Nedbank, which saw its market share rise from 14.0 per cent to 22.3 per cent, almost entirely due to its purchase of BOE. Figure 14 shows the change in market share during this time. The market share shift is most notable at product level, with the crisis leaving a substantial concentration in home loans.

The second 'winner' was African Bank, which was at the time a small unsecured lending business. It purchased the Saambou unsecured lending book at a discount, and this formed the basis of its growth strategy over the next few years.

7 The authorities' response

The curatorship was announced on Monday, 4 February 2002. The pressures on BOE and the other banks began immediately. A further statement made on Thursday, 14 February outlined some of the rationale for the decision (Minister of Finance, 2002). It noted that:

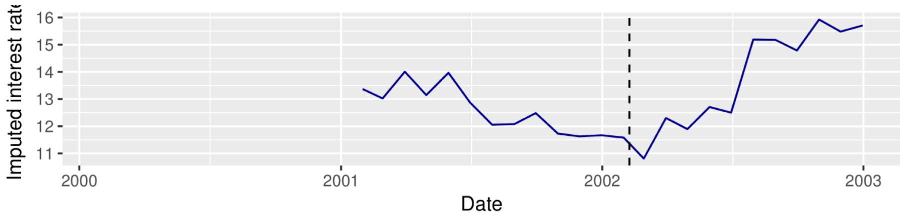
> In examining options, we firmly held the view that to commit Government financial assistance to SAAMBOU Bank would not be prudent as there was no guarantee that those funds would either restore confidence or not be utilised to fund further large net outflows from depositors funds out of the bank.

This statement did not restore confidence to the banking system – quite the opposite as the perception emerged that the authorities would not provide any support to small banks. The situation at BOE deteriorated and all its assets were fully guaranteed, albeit a full month later on 14 March 2002.

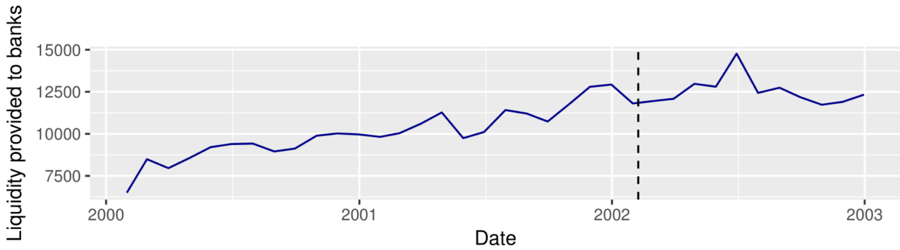
This echoes the inappropriate response by the US Federal Reserve as the Great Depression unfolded, and it is worth repeating this paragraph from Friedman (1968):

> [Money supply] fell not because there were no willing borrowers – not because the horse would not drink. It fell because the Federal Reserve System forced or permitted a sharp reduction in the monetary base, because it failed to exercise the responsibilities assigned to it in the Federal Reserve Act to provide liquidity to the banking system.

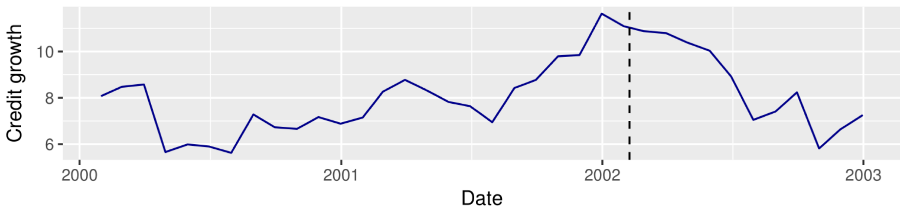
Figure 15 demonstrates that the authorities did not intervene heavily in the market to provide liquidity or ease monetary conditions. Indeed, the repo rate was raised by 400 bps, from 9.5 per cent in December 2001 to 13.5 per cent in September 2002, as the Reserve



(a) Imputed interest rates rose over the course of the crisis, mainly due to repo rate increases. In total the repo rate was raised by 400 bps, from 9.5 per cent in December 2001 to 13.5 per cent in September 2002. Also see Figure 3.



(b) Some additional liquidity was provided to the system, with a small peak in June 2002. However, this liquidity was not widely provided.



(c) Credit growth slowed significantly during the course of the crisis.

Figure 15: Policy response

The central bank did not intervene significantly to provide liquidity or support to the banking sector. In Panel (a), imputed interest rates are calculated as the average interest income as a percentage of assets, providing some indication of the lending rate in the economy.

Source: South African Reserve Bank, monthly data

Bank aimed to dampen the second-round effects of the sharp depreciation in the rand experienced during late 2001.

Institutionally, the way in which the Reserve Bank considered the 2002/3 crisis is borne out by its own subsequent analysis. There is extensive analysis of the crisis in the Bank Supervision Annual Report. However, it is not mentioned in the Monetary Policy Review, nor in the minutes of the monetary policy committee issued on 14 March 2002, in the middle of the crisis. For monetary policy purposes, the authorities appear to have judged that the contraction in credit growth was not due to the crisis. This is despite evidence that the effective interest rate rose and the net interest margin rose, suggesting tighter monetary policy conditions. The credit contraction was in corporate lending, and many of the banks that failed were corporate lenders. Indeed, at its 14 March 2002 meeting, the monetary policy committee raised interest rates by 100 bps. There is, however, a long discussion of the crisis in the 2002 Banking Supervision Annual Report (Registrar of Banks, 2002), produced by a different department in the Reserve Bank. In contrast, the supervision annual report does not discuss credit trends, but rather discusses growth in bank assets. It also notes that some banks received liquidity support, but does not disclose which. In the monthly banking statistics, none of the banks disclose receiving liquidity.

There was substantial engagement between the then Minister, Trevor Manuel and the Reserve Bank about the appropriate course of action. In her biography of Manuel, Green (2012, 506) outlines the disagreement between the Treasury and Reserve Bank. She notes the discovery of a letter from the financial director of Saambou, addressed to the auditors of the bank and to Christo Wiese, the Registrar of Banks. On the basis of the letter, the Treasury concluded that Saambou was insolvent and that liquidity provision would not be an appropriate course of action. The Registrar subsequently indicated that he thought this was the incorrect decision, and that the decision may have led to the run. His summary of the Saambou failure in the Bank Supervision Department's Annual Report (Registrar of Banks, 2002) was also read to imply that he disagreed with the decision, and interviews he gave to the press underlined his view. This evidently led to him being asked to take early retirement – see Mittner (2003*b*).

8 Conclusion

The 2002/3 banking crisis presents an opportunity to better understand bank failures, and draw lessons for the system of financial regulation. The failure was unique internationally – at the time there was little interconnectedness between the banks, South Africa did not have deposit insurance, and there was extensive *ex ante* information available to depositors.

The paper argues that the response of the authorities was inappropriate, and highlighted some coordination weaknesses (between and within institutions). In the year leading up to the small bank crisis, unsecured lending grew by 26.7 per cent, and overall credit growth averaged 9.5 per cent. The central bank, however, reduced the benchmark policy rate. Moreover, the exchange rate depreciated significantly. When the first bank failed in February 2002, the authorities intervened only tentatively – providing a deposit guarantee to one of the large banks. Contagion quickly spread, and faced with a generalised loss of confidence amongst a group of small banks, the authorities did not provide unlimited liquidity support.

The response was within the framework of the 'Greenspan Standard'. In the year leading up to the failure, the central bank did not intervene to slow credit growth, preferring a ‘clean, not lean’. But when the crisis hit, the Reserve Bank progressively increased the overnight policy rate during the course of the crisis, creating potentially greater liquidity pressures. The episode shows the need for a coordinating framework for different functions of the central bank (liquidity provision, monetary policy formulation and banking supervision).

As noted in Havemann (2019), later interventions show that lessons from the small bank crisis appear to have been learnt, and the small bank crisis led to the central bank’s response being substantially more sophisticated.

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Appendix

Table 10: Failed banks, 1990 to 2018

	Bank	Year	Reasons	Intervention
1	Alpha Bank	1990	Fraud	Reserve Bank injected R150m, but bank ultimately liquidated (1993)
2	Cape Investment Bank	1991	Fraud (misstatement of non-performing loans)	Reserve Bank provided R5m for depositors
3	Pretoria Bank	1991	Poor management, merger with Masterbond	
4	Sechold Bank	1994	Bank run liquidity problems (derivatives trading loss)	Liquidity, Investec purchased the bank
5	Prima Bank	1994	Liquidity problems due to non-performing loans	Purchase and assumption (by Unibank)
6	African Bank	1995	Bad management and liquidity problems	Government recapitalised the bank
7	Community Mutual Bank	1996	Liquidity problems due to a very high expense to income ratio	Purchase and assumption (by Unibank)
8	Islamic bank	1997	Poor management and improper accounting, particularly around unsecured lending	Liquidated
9	FBC Fidelity Bank	1999	Poor management and liquidity problems	
10	Regal Treasury Bank	2002	Auditors (EY) rescinded their audit approval, precipitating a run	Liquidated
11	New Republic Bank	2002	Poor management and liquidity problems	Liquidated

12	Saambou Bank	2002	Por management	See chapter 2
13	BOE Bank		Contagion	
14	Cadiz Investment Bank		Contagion	
15	FirstCorp Merchant Bank		Contagion	
16	International Bank of Southern Africa		Contagion	
17	Merril Lynch Capital Markets Bank		Contagion	
18	Brait Merchant Bank		Contagion	
19	CorpCapital Bank		Contagion	
20	Old Mutual Bank		Contagion	
21	PSG Investment Bank		Contagion	
22	TA Bank of Southern Africa		Contagion	
23	African Merchant Bank	2003	Contagion	
24	Cape of Good Hope Bank		Contagion	
25	ING Bank NV SA Branch		Contagion	
26	Nedcor Investment Bank		Contagion	
27	RMB Asset Finance Bank		Contagion	
28	Securities Investment Bank		Contagion	
29	Unibank		Contagion	
30	African Bank	2014	Bad management and liquidity problems, particularly around unsecured lending	See chapter 4
31	VBS Mutual Bank	2018	Fraud	Currently underway

Source: Blackbeard (2014) quoted in Tjiane (2015). For failures during the 1800s, see Arndt (1928) and for the 1970s, see Koseff (1984).

Table 11: Banks in data set – Liabilities

Balance sheet item	All 31/01/2002 Total	Failed All failed	Saambou 31/01/2002	First Wave (incl BOE) 31/01/2002	Second Wave 31/01/2002	Survive All
Group NCDs	3.9	0.0	0.0	0.0	0.0	3.9
Group funding - other	15.5	2.5	0.0	0.2	2.3	13.0
Interbank - NCDs	24.2	1.6	0.0	1.6	0.1	22.6
Interbank - other	25.7	2.9	1.0	1.3	0.6	22.8
Government	45.9	2.2	0.4	1.6	0.3	43.7
- Local government	11.3	1.2	0.4	0.5	0.3	10.1
- Financial public corporations	6.2	0.3	0.0	0.3	0.0	5.8
- Non financial public corporations	13.1	1.5	0.1	1.2	0.2	11.7
Insurers	34.9	2.6	0.6	1.7	0.2	32.4
Pension funds	14.6	1.8	0.0	1.6	0.3	12.8
Other financial institituions	104.3	17.4	0.0	16.0	1.3	86.9
Non-financial	172.0	11.6	3.6	6.8	1.1	160.5
Unincorporated business	26.7	0.4	0.0	0.3	0.1	26.3
Individuals	156.7	24.1	8.9	14.4	0.8	132.5
Non-profits	18.9	2.9	0.4	2.4	0.1	16.0
Non-residents	24.7	0.1	0.0	0.1	0.0	24.6
Reserve Bank	0.0	0.0	0.0	0.0	0.0	0.0
Short-term deposits	0.0	0.0	0.0	0.0	0.0	0.0
Other	97.4	5.8	0.0	4.6	1.2	91.6
Other to public	4.0	0.1	0.0	0.0	0.1	3.9
Total to public	851.3	79.8	15.5	55.0	9.3	771.5
	3.6	0.0	0.0	0.0	0.0	3.6
Other liabilities	90.8	3.7	0.3	1.3	2.0	87.2
Total Liabilities	945.7	83.5	15.8	56.4	11.4	862.2
Summary of liabilitiies	0.0	0.2	0.0	0.0	0.2	-0.2
Intergroup	19.4	2.5	0.0	0.2	2.3	16.8
Interbank	49.9	4.6	1.0	2.9	0.6	45.4
Public	76.5	5.3	0.9	3.6	0.8	71.2
Financial	153.8	21.8	0.6	19.3	1.9	132.1
Nonfinancial	172.0	11.6	3.6	6.8	1.1	160.5
Individuals	183.3	24.5	8.9	14.7	0.9	158.8
Nonprofit	18.9	2.9	0.4	2.4	0.1	16.0
Nonres	24.7	0.1	0.0	0.1	0.0	24.6
Other	195.8	9.6	0.3	5.9	3.4	186.2

Table 12: Banks in data set – Assets

	All 31/01/2002 Total	Failed All failed	Saambou 31/01/2002 SAAMBOU	First Wave (incl BOE) 31/01/2002 First wave	Second Wave 31/01/2002 Second wave	Survive All
All assets	19.6	2.0	0.4	1.4	0.2	17.6
Bank group assets	20.8	0.2	0.0	0.1	0.1	20.6
Interbank	38.2	3.4	0.7	1.5	1.2	34.9
Foreign	2.4	0.0	0.0	0.0	0.0	2.4
Resale agreemnts	16.1	0.7	0.0	0.0	0.7	15.3
Installments	96.0	5.2	1.6	2.8	0.8	90.7
Mortgages	254.6	41.9	8.4	33.1	0.5	212.7
Credit Cards	13.8	0.5	0.1	0.3	0.2	13.3
Commercial debts	18.0	1.1	0.7	0.2	0.1	16.9
Foreign currency loans	131.0	0.5	0.0	0.5	0.0	130.4
Redeemable preference shares	14.8	1.8	0.2	1.6	0.0	13.0
Public sector	7.8	0.0	0.0	0.0	0.0	7.8
Overdrafts - non-banks	26.4	0.0	0.0	0.0	0.0	26.3
Non-financial companies	50.0	1.9	0.0	1.9	0.0	48.1
Unincorporated business	8.0	0.1	0.0	0.1	0.0	7.9
Individuals	13.8	0.3	0.0	0.3	0.0	13.5
Non-profits	1.0	0.2	0.0	0.2	0.0	0.8
Factoring	2.4	0.7	0.0	0.4	0.2	1.7
Other - non-bank private sector	16.9	1.8	0.0	1.0	0.8	15.1
Non-financial companies	70.5	7.7	0.2	6.6	0.8	62.9
Unincorporated business	6.1	0.2	0.0	0.1	0.1	5.9
Individuals	25.8	10.9	4.7	1.2	5.0	14.9
Non-profits	2.8	0.1	0.0	0.1	0.0	2.6
Specific provisions	-13.9	-2.2	-0.6	-1.1	-0.5	-11.6
Other assets	137.0	11.5	0.0	8.0	3.5	125.5
TOTAL ASSETS	1039.3	95.1	17.1	63.7	14.3	944.2
Summary assets						
Central bank money	19.6	2.0	0.4	1.4	0.2	17.6
Deposits, loans and advances	823.1	76.9	16.0	51.0	10.0	746.2
Investments and portfolio assets	137.0	11.5	0.0	8.0	3.5	125.5
Non-financial assets	11.6	1.2	0.1	1.1	0.1	10.4
Other assets	47.9	3.4	0.6	2.2	0.6	44.5
Interbank	61.5	3.6	0.7	1.6	1.3	57.9
Vehicle	112.1	6.0	1.6	2.8	1.5	106.1
Mortgages	254.6	41.9	8.4	33.1	0.5	212.7
Credit card	13.8	0.5	0.1	0.3	0.2	13.3
Companies	96.8	10.4	0.2	8.3	1.9	86.4
Other	298.3	16.8	5.6	6.0	5.2	281.5
NPLs - specific	-13.9	-2.2	-0.6	-1.1	-0.5	-11.6
Other assets	216.1	18.1	1.1	12.8	4.3	198.0