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Measuring Real Capital Adequacy in Extreme Economic Conditions: An Examination of the Swiss Banking Sector*

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The global financial crisis (GFC) has placed the creditworthiness of banks under intense scrutiny. In particular, capital adequacy has been called into question. Current capital requirements make no allowance for capital erosion caused by movements in the market value of assets. This paper examines default probabilities of Swiss banks under extreme conditions using structural modeling techniques. Conditional Value at Risk (CVaR) and Conditional Probability of Default (CPD) techniques are used to measure capital erosion. Significant increase in Probability of Default (PD) is found during the GFC period. The market asset value based approach indicates a much higher PD than external ratings indicate. Capital adequacy recommendations are formulated which distinguish between real and nominal capital based on asset fluctuations.

Keywords: real capital, financial crisis, conditional value at risk, credit risk, banks, probability of default, capital adequacy

Introduction

This study examines fluctuations in bank asset values and default probabilities prior to and during the financial crisis, in a Swiss setting. These asset value fluctuations are used as a nominal capital deflator to determine real capital adequacy. Recommendations are made regarding capital buffers to counter these fluctuations.

Switzerland is one of the world's most important banking centres, with an enviable reputation for prudency and discreetness. Besides the United States, it is the only country to have two cities, Geneva and Zurich, achieve a top 10 ranking by the Global Financial Centres Index (ZYen and the City of London, 2009). The banking industry is of crucial importance to Switzerland. The Central Bank, the Swiss National Bank (SNB), noted in their Financial Stability Report (2009) that the banking sector's total assets amount to eight times GDP, the largest ratio of all the G10 countries. In comparison, the United States has a ratio of approximately 1x GDP and the UK 4x.

The Swiss banking sector, as reported by the SNB (2009), has four main bank categories. Firstly, the sector is dominated by two big banks, UBS and Credit Suisse, which make up 76% of total banking sector asset values but only 34% domestic lending share due to their large international presence. Then there are 24 Cantonal banks with a domestic lending market share of 34%. The balance of the sector is made up of 367

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independent bank members of the Raiffeisen group and 75 regional banks.

In line with the global banking industry, Switzerland banks have been severely affected by the financial crisis, with large losses incurred by the major banks. Globally, governments have introduced measures to support troubled banks. Examples include the 2008 US $700bn Troubled Asset Relief (TARP) programme and the 2008 UK £500bn financial support package. In Switzerland, rescue has primarily surrounded the largest bank, UBS. In 2008 a package was put together to allow a SFr6bn capital injection into UBS and the transfer of USD $60bn of troubled assets to a special purpose vehicle of the SNB. Regulators in Switzerland have moved to shore up capital adequacy requirements. The Swiss Financial Market Supervisory Authority (FINMA) has introduced capital adequacy requirements for the big banks above the minimum required by Basel, as well as a minimum leverage ratio of 3%, measured as Tier 1 capital to total assets (this ratio was 2.9% for Credit Suisse at end 2008, and 1.6% for UBS). These new requirements are to be implemented by 2013. It is expected that in good times the ratios will be well above these minimum levels.

Leverage in European banks is typically high compared to US banks. The aggregated equity of Swiss banks in this study is 3.5% of total assets, compared to 4.2% for a pool of the world's 20 largest non-Swiss banks. US banks in the pool have an equity ratio of 7.1%, Asian banks 3.6%, UK banks 4.4%, and other European banks 3.2%. The big two Swiss banks have a smaller combined equity ratio (2.8%) than the remaining Swiss banks (6.5%). Tier 1 Capital ratio to risk weighted assets is 11.5% for the combined big Swiss banks and total capital to risk weighted assets is 15.6%. These ratios are higher than for either US or UK banks, indicating a lower risk weighting is being applied by Swiss banks. Concerns over high leverage and major differences between risk weighted and absolute ratios have led to concerns over the Basel approach. The SNB has been at the forefront of calls for a leverage ratio to be introduced by Basel. Blum (2007) argued, that despite a leverage ratio being a blunt instrument which does not differentiate between risk profiles of banks, it has the advantage of inducing truthful risk reporting where supervisors have a limited ability to identify or sanction dishonest banks. Hildebrand (2008) viewed excessive leverage as a main cause of financial fragility. He viewed a simple leverage ratio as a safety valve against shortcomings of risk weighted adjustments, and ensuring a minimal capital buffer is maintained against unexpected losses and underestimation of risk.

Others have expressed concerns that reducing asset values in times of crisis reduce equity levels. The Bank of England (2008) is concerned that not only do asset values reduce in times of uncertainty, but rising default probabilities make it more likely that assets have to be liquidated at market values, providing a need for increased countercyclical capital. This of course has the downside that banks would have to bear the cost of "buffer" capital in upside times, but the key purpose of capital adequacy is that buffers are available to absorb risk when required. The IMF (Caruana & Narain, 2008) maintained that the need for banks to have a robust capital regime adequate to the risks they face, including business cycle risk, is borne out by the problems banks faced over the GFC, and that "as the experiences of some large international banks in the current turmoil have shown, the benefits of being able to access capital rapidly in bad times may outweigh the costs of having to hold capital buffers through the cycle". Basel II emphasized that volatility should be addressed in capital allocation and that strategic plans should take into account capital needs especially in a stressful economic environment (Caruana & Narain, 2008). Indeed, proposed amendments to Basel II (i.e., Basel III) include the introduction of a capital buffer requirement following earlier identification by the Basel Committee on Banking Supervision (2008) for the need for "a series of measures to promote the build-up of capital buffers in good times that can be drawn upon in periods of stress, a countercyclical capital framework will contribute to a more stable banking system, which will help dampen, instead of amplify, economic and financial shocks”. The Basel III capital buffer is however a static percentage, which does not obviate the need for banks to measure and manage their capital requirements, which may well above the regulatory minimum. This paper assists this process by providing a metric for measuring potential capital buffer requirements.

The linkage between asset values, economic cycles and default probabilities is discussed by several authors. Examples include the structural models of Merton (1974) and KMV (Crosbie & Bohn, 2003) which incorporate asset value fluctuations and which are dealt with in depth in this paper. Jarrow (2001) incorporated equity prices into the estimation of default probabilities, where recovery rates and default probabilities are correlated and depend on the state of the macroeconomy. Using structural analysis Allen and Powell (2009) and Powell and Allen (2009) found no significant correlation between industry default probabilities over time and between economic cycles. In focusing on the impact of fluctuating asset values on default probabilities and capital adequacy, this study compares Swiss banks to a “pool” of Global banks. The study uses CVaR to measure the most extreme of asset value fluctuations. The following section outlines benefits and contributions of the study, followed by discussion on VaR and CVaR. PD is discussed thereafter, giving consideration to Basel measurements for banks, and the structural models of Merton and KMV. This is followed by Data and Methodology, and then the Results (which also examines whether current bank credit ratings are consistent with PD values). Conclusions are provided in the final section, which also includes recommendations for a revised capital adequacy framework based on our findings. The study does not make any representations about default probabilities of any individual banks. It is also noted that default probabilities calculated using structural methodology are based on available balance sheet and equity price information, and do not take into account external options available to banks for reducing default probability such as additional capital raising or government intervention.

Contribution and Benefits of the Study

Firstly, the study can benefit regulators and banks by providing new credit risk methodologies which incorporate CVaR into PD calculations using the unique CPD methodology of the authors to measure extreme risk. Not only is risk being measured during the extreme conditions of the global financial crisis, but asset values are being measured at their utmost fluctuation levels using CPD. It is during adverse conditions when default is most likely to occur.

Secondly, a further novel concept introduced in this study is the use of VaR and CVaR techniques to distinguish between real and nominal capital, and to formulate capital adequacy recommendations based on real equity levels.

Thirdly, the techniques could also be generalized in future studies to other banks besides Swiss banks, or corporate borrowers in assessing default probabilities.

Finally, insight is provided into how the Swiss banking industry has been affected by extreme asset fluctuations compared to US and other European markets.

VaR and CVaR

Value at Risk (VaR) is well understood and widely applied by the banking industry for measuring market risk and determining capital adequacy. VaR measures potential losses at a given level of confidence for a specific time period. There is extensive literature coverage on VaR. Examples include Jorion (1996), RiskMetricsTM of Morgan and Reuters (1996), as well as discussion by more than seventy recognized authors in the VaR Modeling Handbook and the VaR Implementation Handbook (Gregoriou, 2009a; 2009b).

VaR has received widespread criticism since the onset of the global financial crisis. The banking industry is perceived to have placed overreliance on VaR models which focus on historical losses and which do not incorporate a measure of tail risk. Well before the financial crisis, VaR was found to have shortcomings. Artzner, Delbaen, Eber, and Heath (1997; 1999) found VaR to have certain undesirable mathematical properties, such as lack of sub-additivity, convexity and monotonicity. Analysts at Standard & Poor's (Samanta, Azarchs, & Hill, 2005) found VaR to have severe limitations which they believe could lull a company into a false sense of security. They report that VaR does not provide consistent measures of risk appetite across institutions due to varying assumptions used in its calculation. In addition VaR ignores tail risk, which is especially important under abnormal market conditions, and the S&P analysts report concluded that VaR should ideally be used in conjunction with other measures.

One measure which does measure tail risk is Conditional Value at Risk (CVaR), which measures losses beyond VaR. If VaR is measured at a 95% confidence level, then CVaR measures the tail 5% returns. CVaR has been proved to be a coherent risk measure (Pflug, 2000), which does not show the undesirable mathematical properties of VaR. A number of papers apply CVaR to portfolio optimization problems, for example Rockafellar and Uryasev (2002; 2000), Andersson, Uryasev, Mausser, and Rosen (2000), Alexander, Coleman, and Li (2003), Alexander and Baptista (2003), Rockafellar, Uryasev, and Zabarankin (2006) and Menoncin (2009).

Probability of Default

We commence this section with a discussion on Basel requirements for bank counterparties as per the Bank for International Settlements (2004). We then discuss the background to the structural methodology used in this study.

Basel and Bank Exposures

Basel requires banks to calculate Tier 1 and Total Capital as a percentage of risk weighted assets. For bank counterparties, risk weightings can be calculated using either the Standardized or Internal Ratings Based (IRB) approach. The standardized approach relies on external ratings for corporates and banks, with lower weightings applied to some bank categories as compared to corporates, as shown in Table 1.

Table 1

Basel II Risk Weights

Credit assessment	AAA to AA-	A+ to A-	BBB+ to BB-	BB+ to B-	Below BB-	Unrated
Corporate risk weight	20%	50%	100%	100%	150%	100%
Bank risk weight	20%	50%	50%	100%	150%	50%

According to Bank for International Settlements (2004):

> Basel Capital requirements are based on capital (Tier 1 and Total capital) as a percentage of risk weighted assets. The percentages show the risk weightings that must be applied to the assets for the purpose of calculating capital allocation. The Corporate risk weightings do not include exposures to small business. The bank risk weightings are those that must be applied to Bank counterparties.

Adjustments are applied according to circumstances. For example, lending secured by residential property is weighted at 35%, and by commercial property 100%. Past due loans are weighted at 100%-150% depending on specific provisions. Banks using an IRB approach must use it across the entire banking group. For corporate, sovereign, and bank exposures, data under the advanced approach must cover one business cycle but must in any case be at least seven years. The capital requirement (K) is calculated as a function of:

P	Probability of default (also often referred to as PD);
LGD	Loss given default;
EA	Exposure at default;
M	Effective maturity (in some cases).

This approach has two levels—foundation and advanced. Under the foundation approach, banks generally provide their own *P* and rely on supervisory estimates for other components. Under the advanced approach, banks provide more of their own estimates of *P*, *LGD*, *EA*, *M*, subject to meeting certain standards.

Structural Models and PD

Using the option pricing methodology of Black and Scholes (1973), the Merton (1974) structural model assumed that the firm has one single debt issue and one single equity issue. The debt (*D*) is consistent with a zero coupon bond that matures at time (*T*). The initial position (asset value) of the firm is:

$$A_0 = E_0 + D_0 \tag{1}$$

At *T*, the firm pays off the bond, with remaining equity paid to the shareholders. The firm defaults if the debt obligation exceeds the asset value of the firm at *T*. In this case the bondholders take ownership of the firm and the shareholders get nothing (due to limited liability of shareholders the amount will not be negative). The amount paid to bondholders = *b*. Equity at *T* (remaining value payable to the shareholders) is as follows:

$$E_T = A_T - b \tag{2}$$

where the debt value is greater than the asset value, then $E_T = 0$. Thus the value of a firm's stock at debt maturity:

$$E_T = max\ (A_T - b,\ 0) \tag{3}$$

This is the same as the payoff of a call option on the firm's value with strike price b. A call option gives the holder the right to buy a certain quantity (usually 100 shares) of an underlying security from the writer of the option, at a specified price (the strike price) up to a specified date (the expiration date). If, at *T*, assets exceed loans, the owners will exercise the option to repay the loans and keep the residual as profit. If loans exceed assets, then the option will expire unexercised and the owners (who have limited liability) default. The call option is in the money where $A_T - b > 0$, and out the money where $A_T - b < 0$.

Under the KMV model, probability of default *PD* is a function of the distance to default *DD* (number of standard deviations between the value of the firm and the debt) determined by using the market value of assets (*A*), less the amount of debt (*b*) divided by the volatility of assets σ_A.

$$\frac{A - b}{\sigma A} \tag{4}$$

PD can be determined using the normal distribution. For example, if *DD* = 2 standard deviations, we know there is a 95% probability that assets will vary between one and two standard deviations. There is a 2.5% probability that they will fall by more than two standard deviations.

KMV found that the normal distribution approach followed by Merton results in *PD* values much smaller than defaults observed in practice. KMV has a large worldwide database from which to provide empirically based Estimated Default Frequencies (EDF). For example, KMV found that historical data shows that firms with a *DD* of 4 have an average default rate of approximately 1% and therefore assign an EDF of 1% to firms with this *DD*. By comparison, the normal distribution approach yields a *PD* of almost 0 for this *DD* (Crosbie & Bohn, 2003). In KMV, *b* is the value of all short-term liabilities (one year and under) plus half the book value of long term debt outstanding. *T* is usually set as one year. Thus the KMV model consists of three steps. Firstly, estimate market value and volatility of firm's assets. Secondly, calculate *DD*. Thirdly, match distance to default to an empirically obtained EDF.

Merton assumes that asset values are log normally distributed. Distance to default and probability of default are calculated as:

$$DD = \frac{\ln(A/F) + (\mu - 0.5\sigma_V^2)T}{\sigma_V \sqrt{T}} \tag{5}$$

$$PD = N(-DD) \tag{6}$$

where A = market value of firms assets, F = face value of firm's debt, μ = an estimate of the annual return (drift) of the firm's assets, N = cumulative standard normal distribution function. Different aspects of credit risk using structural methodology have been examined by several authors, such as asset correlation (Cespedes, 2002; Kealhofer & Bohn, 1993; Lopez, 2004; Vasicek, 1987; Zeng & Zhang, 2001), predictive value and validation (Bharath & Shumway, 2008; Stein, 2007), Australian and US markets (Allen & Powell, 2009; Powell & Allen, 2009), fixed income modeling (D'Vari, Yalamanchili, & Bai, 2003), default probabilities and capital (Bischel & Blum, 2004) and the effect of default risk on equity returns (Gharghori, Chan, & Faff, 2007; Vassalou & Xing, 2002).

Data and Methodology

Data

The study compares Swiss banks to a "pool" of global banks. Fifteen years of equity data is obtained from Datastream, together with current balance sheet data on equity and debt. Swiss banks include listed banks for which equity prices and Worldscope balance sheet data are available in Datastream. This involves 24 Swiss banks with total assets of CHF 4.5 trillion. The "pool" comprises the 20 largest banks in the world (aside from Swiss banks and also excluding Chinese banks for which an insufficient length of data is available). The "pool" is summarized in Table 2.

Table 2
"Pool" of Banks Used in This Study

Region	Number of banks	Assets USD $tr
U.S.	4	6.04
U.K.	4	4.66
Other European	9	16.86
Asian	3	4.91

There are 20 Banks included in our Banking Pool. This consists of the world's largest non-Swiss Banks. Chinese banks are also excluded, due to insufficient length of equity information. A full listing of Swiss and Pool banks is contained in Table 3.

Swiss Banks include all listed banks for which Equity and WorldScope balance sheet data is available on Datastream. Pool banks include the 20 largest Global non-Swiss banks by total asset values for which equity and balance sheet data is also available on Datastream. Inclusions are similar to lists of the largest world banks provided by other sources (Bankers Almanac, 2009; The Banker, 2009), but Chinese banks are excluded due to insufficient historical equity data.

Table 3
List of Banks Used in This Study

Swiss banks	Pool banks	Country
Bank CA St. Gallen	Banco Santander	Spain
Bank Linth	Bank of America	U.S.
Bank LLB	Barclays Bank	U.K.
Bank Sarasin	BNP Paribas	France
Banque Cantonale de Genève	Citigroup	U.S.
Banque Cantonale du Jura	Commerzbank	Germany
Banque Cantonale Vaudoise	Credit Agricole	France
Basellandschaftliche Kantonalbank	Deutsche Bank	Germany
Basler Kantonalbank	Dexia	Belgium
BEKB/BCBE	HSBC Holdings	U.K.
Coop Bank	ING Bank	Netherlands
Credit Suisse Group	JP Morgan	U.S.
EFG International	Lloyds TSB	U.K.
Graubündner Kantonalbank	Mitsubishi UFJ	Japan
Hypothekarbank Lenzburg	Mizuho Financial Group	Japan
Luzerner Kantonalbank	Royal Bank of Scotland	U.K.
Neue Aargauer bank	Societe Generale	France
Schwyzer Kantonalbank	Sumitomo Mitsui	Japan
St.Galler Kantonalbank	UniCredit	Italy
UBS AG	Wells Fargo	U.S.
Valiant Bank		
VP Bank		
Walliser Kantonalbank		
Zuger Kantonalbank		

VaR and CVaR Methodology

We use the parametric method of RiskMetrics (Morgan & Reuters, 1996) who introduced and popularised VaR. We calculate the logarithm of price relatives every day for each bank for the past 15 years. Based on a normal distribution, the standard deviation is multiplied by 1.645 to obtain VaR at 95% confidence level. As we are not calculating VaR for investment purposes, we do not need to show the effect of portfolio diversification. We therefore use an undiversified approach, whereby total VaR is the asset weighted average of the individual bank VaRs. CVaR is calculated as the average of the worst 5% of returns (i.e., returns beyond VaR.)

Structural Methodology

We apply the Merton methodology previously discussed in the Structural Models and PD section. An initial estimation for asset returns is made using the equity volatility (obtained as discussed in the VaR and CVaR Methodology section) and multiplying it by equity as a percentage of asset value. The daily log return is calculated and new asset values estimated. This is applied for every day. Following KMV, this process is repeated until asset returns converge. In order to measure *DD* at the most extreme of the asset value fluctuations, we also incorporate CVaR methodology into the structural model. We substitute the standard deviation of all returns with the standard deviation applying to the most extreme 5% of returns (CStdev) to calculate a conditional *DD* (*CDD*) and conditional *PD* (*CPD*) as follows:

$$CDD = \frac{\ln(V/F) + (\mu - 0.5\sigma_V^2)T}{CStdev_V \sqrt{T}} \tag{7}$$

$$CPD = N\ (-DD) \tag{8}$$

Results

Table 4 shows Daily VaR and CVaR. VaR is calculated on a parametric basis, whereby the standard deviation of daily returns is multiplied by 1.645 (being 95% confidence level based on a normal distribution). Annual VaR can be obtained by multiplying Daily VaR by the square root of 250. Figures are undiversified and represent the weighted average of the individual Bank VaRs. CVaR is calculated as the average of the worst 5% of actual returns (those beyond the 95% VaR).

Table 4
VaR and CVaR—Results Summary

Year	Swiss banks		Pool	
	Daily VaR	Daily CVaR	Daily VaR	Daily CVaR
2008	0.0791	0.1117	0.1127	0.1584
2007	0.0418	0.0609	0.0444	0.0597
2006	0.0195	0.0272	0.0176	0.0249
2005	0.0213	0.0301	0.0192	0.0266
2004	0.0143	0.0190	0.0154	0.0215
2003	0.0194	0.0261	0.0206	0.0283
2002	0.0364	0.0515	0.0352	0.0481
2001	0.0402	0.0569	0.0437	0.0621
2000	0.0369	0.0544	0.0412	0.0573
1999	0.0278	0.0398	0.0396	0.0534
1998	0.0293	0.0386	0.0393	0.0524
1997	0.0474	0.0716	0.0494	0.0706
1996	0.0276	0.0386	0.0361	0.0504
1995	0.0174	0.0270	0.0242	0.0336
1994	0.0175	0.0236	0.0256	0.0353

VaR and CVaR results are summarized in Table 4 which shows how both VaR and CVaR reduced over the boom times in the mid 2000's and then spiked during the Global Financial Crisis (GFC) period, dramatically so in 2008. It is also interesting to note that volatility is noticeably lower for Swiss banks during the GFC period. CVaR is much higher than VaR, especially during the GFC period. Figure 1 illustrates these trends with three point polynomial trend lines.

The figure compares Daily VaR and CVaR between the Swiss Banks and the pool of European Banks using an order three polynomial trend line. VaR is calculated on a parametric basis, whereby the standard deviation of daily returns is multiplied by 1.645 (being 95% confidence level based on a normal distribution). Annual VaR can be obtained by multiplying Daily VaR by the square root of 250. Figures are undiversified and represent the weighted average of the individual Bank VaRs. CVaR is calculated as the average of the worst 5% of actual returns (those beyond the 95% VaR).

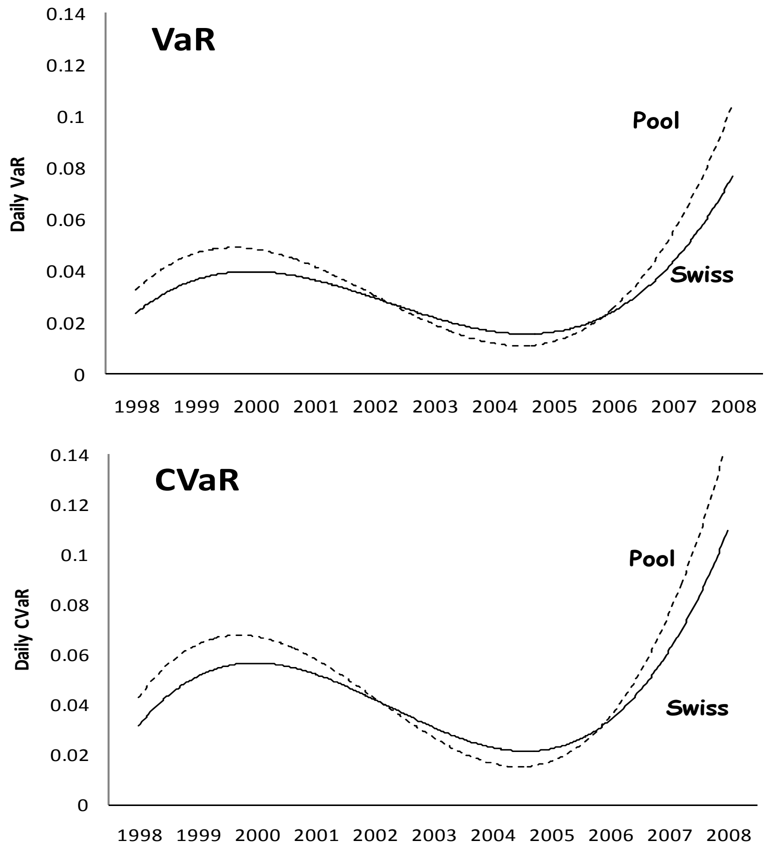


Figure 1. Daily VaR and CVaR between the Swiss banks and the pool of European banks.

Up to this point, we have only focused on fluctuations in equity values, which are an important component of default probability. We now analyze the results of our structural modeling. This is summarized in Table 5.

Table 5

Distance to Default—Results Summary

	Swiss banks				Pool			
	DD	*PD*	*CDD*	*CPD*	*DD*	*PD*	*CDD*	*CPD*
2008	0.94	0.1729	0.24	0.4037	0.68	0.2486	0.16	0.4359
2007	1.86	0.0315	0.46	0.3215	1.87	0.0305	0.48	0.3172
2006	4.06	0.0000	1.04	0.1491	4.66	0.0000	1.14	0.1262
2005	3.72	0.0001	0.96	0.1691	4.12	0.0000	1.03	0.1513
2004	5.46	0.0000	1.46	0.0723	5.28	0.0000	1.31	0.0958
2003	4.04	0.0000	1.08	0.1406	3.60	0.0002	0.89	0.1864
2002	2.25	0.0123	0.58	0.2820	2.15	0.0160	0.54	0.2958
2001	1.99	0.0231	0.51	0.3054	1.84	0.0332	0.45	0.3269
2000	2.35	0.0094	0.58	0.2817	1.88	0.0302	0.45	0.3269
1999	2.68	0.0036	0.68	0.2471	1.93	0.0266	0.48	0.3161
1998	2.54	0.0055	0.71	0.2400	1.95	0.0257	0.49	0.3127
1997	1.58	0.0576	0.38	0.3518	1.55	0.0606	0.36	0.3588
1996	2.70	0.0034	0.71	0.2403	2.12	0.0170	0.51	0.3060
1995	4.29	0.0000	1.01	0.1570	3.16	0.0008	0.76	0.2234
1994	4.27	0.0000	1.15	0.1246	2.99	0.0014	0.72	0.2348

Calculations are described in earlier sections. *DD* shows the number of standard deviations to default of the market value of assets. Default occurs when the firm's debt exceeds asset values. Debt is measured as current debt plus 50% of long term debt. Prior year figures calculate the distance to default of current balance sheet values based on historical fluctuations in asset values. *CDD* and *CPD* are calculated as for *DD* and *PD*, but based on the worst 5% of asset returns.

Both the Pool and Swiss banks show a dramatic jump in default probabilities in 2008, with *DD* falling below one standard deviation, although the *PD* is slightly lower for Swiss banks. *CPD* values exceed 40% for Swiss and Pool banks. Swiss *DD* and *CPD* trends are shown in Figure 2 and compared to the Pool in Figure 3.

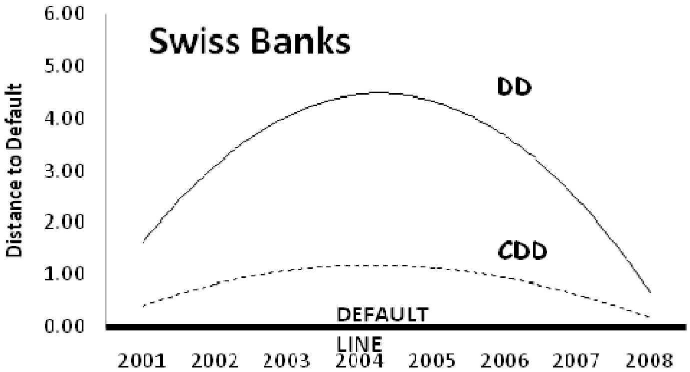


Figure 2. DD and CDD of Swiss banks.

The figure compares Distance to Default (*DD*) and Conditional Distance to Default (*CDD*) of Swiss banks. *DD* is calculated using Merton structural methodology, and shows the number of standard deviations to default of the market asset of assets, with default occurring when the firm's debt exceeds asset values. *CDD* is calculated as for *DD* but based on the worst 5% of asset returns. The order three polynomial trendline shows how distance to default increased over the mid-2000s and reduced during the GFC.

Swiss banks show a fairly similar default trend to the pool (for *DD* and *CPD*), with *DD* increasing during the mid-2000's and decreasing dramatically during the GFC. Whilst in earlier years, default distance was further than the pool, this has narrowed during the mid to late 2000's. However, if we analyze the components of distance to default, then we see this similarity in default distances between Swiss and Pool banks is caused by different factors. *DD* is a function of two key components: leverage and asset volatility. For example, in a bank with equity of 10%, if market value of assets reduces by 10% then the default line is breached.

Figure 3 compares Distance to Default (*DD*) and Conditional Distance to Default *CDD* between Swiss banks and the Pool of European banks. *DD* is calculated using Merton structural methodology, and shows the number of standard deviations to default of the market asset of assets, with default occurring when the firm's debt exceeds asset values. *CDD* is calculated as for *DD* but based on the worst 5% of asset returns. The order 3 polynomial trendline shows how distance to default increased over the mid-2000s and reduced during the GFC. A similar trend is noted for Swiss banks and Pool banks, with Pool banks showing a somewhat higher probability of default than Swiss banks during downturn periods of the early 2000's.

The figure shows market asset VaR (99% level) for years 2000-2008 (represented by the "waves") superimposed on fixed bank market equity levels (represented by the "cones"). In this diagram we define market equity per KMV as the distance between market asset values and debt (debt being current debt plus half of long term debt). Default occurs when the wave level rises above the cone level. Using VaR, this comes closest to happening in 2008. If CVaR were used, the waves are at higher levels.

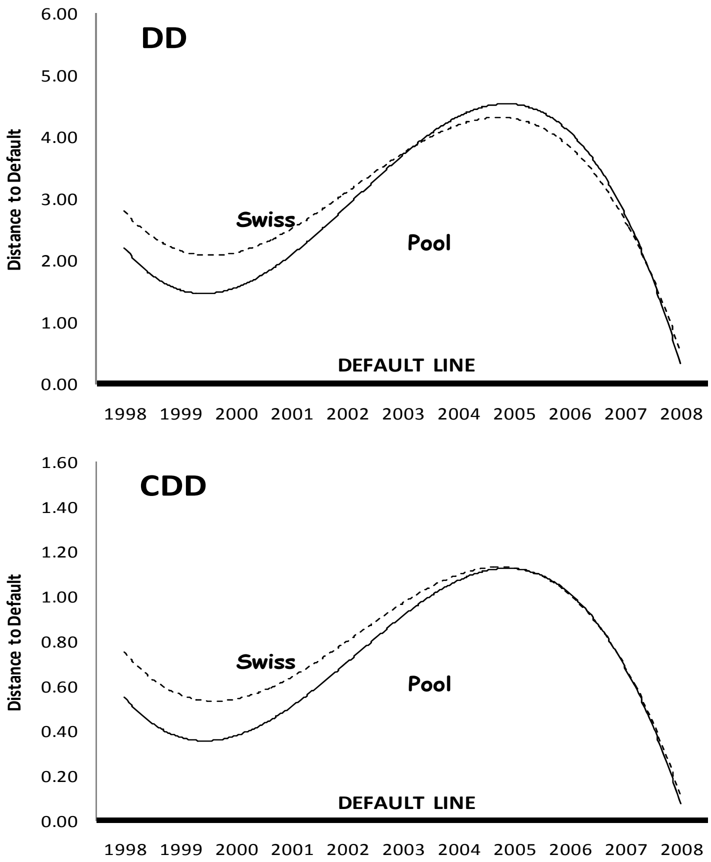


Figure 3. DD and *CDD* between Swiss banks and the Pool of European banks.

Figure 4 shows the relationship between equity, market value of assets and *DD*. In 2008, *DD* levels for Pool and Swiss banks are very similar. Pool market equity is approximately 10% with Swiss market equity approximately 8%. Therefore Swiss banks have a shorter distance to travel to default. However, Swiss Asset VaR is lower. Asset VaR peaks in 2008 at approximately 6% for the pool, and 4% for Swiss banks. The combination of lower market equity, lower VaR for Swiss banks results in a similar *DD* to the higher capital, higher VaR combination of Pool banks.

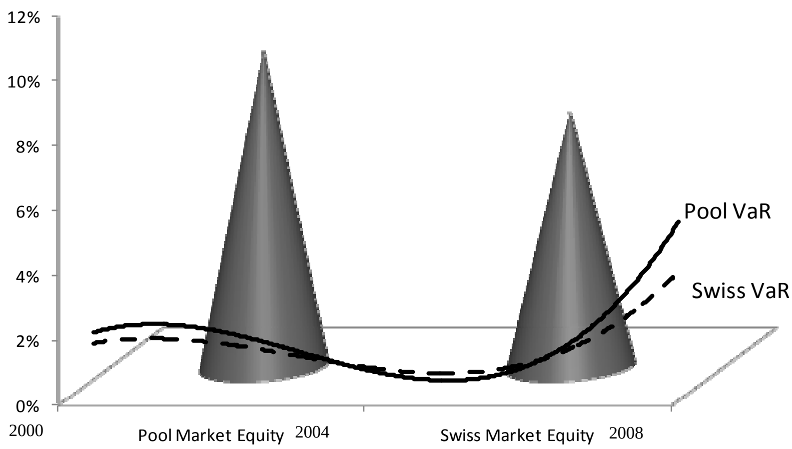


Figure 4. VaR at pool market and Swiss market.

Standard & Poor's (2008) provided transition default probabilities associated with credit ratings. Almost all the banks in our sample of Swiss and Pool banks carry a credit rating above BBB, equating to transition to default probabilities of less than 0.5% for 2008. This is significantly lower than the default calculated in Table 5 based on fluctuating asset values.

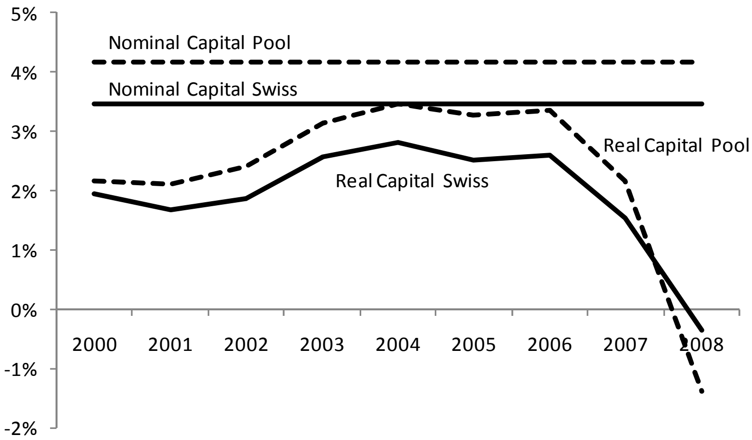
We now examine impacts of market movements on capital adequacy. If market asset values reduce by 10% (VaR is 10%), then in real terms capital also reduces by 10%. Current capital requirements for banks are based on book values (nominal values) as opposed to market values (real values). It needs to be made clear here that whilst capital adequacy requirements do have a market risk component, this is related to market movements in interest rates or foreign exchange or share investments, not the asset and equity values of the banks themselves, meaning that calculating capital buffer based on movements in bank asset values does not constitute any double counting. Therefore real capital (*Kr*) can be measured as nominal capital requirement (*K*) less market asset VaR. Alternatively, Asset CVaR (CStdev) can be used, giving a more conservative measure, shown for Company *x* as follows:

$$Kr_x = K_x - CStdev_x \tag{9}$$

To cover these asset value movements, required capital (K^*) should be increased by the fluctuating asset value. For Company *x*, this is depicted as follows:

$$K^*_x = K_x + CStdev_x \tag{10}$$

The relationship between real and nominal capital is shown in Figures 5-6.



Figures 5. Relationship between real and nominal capital.

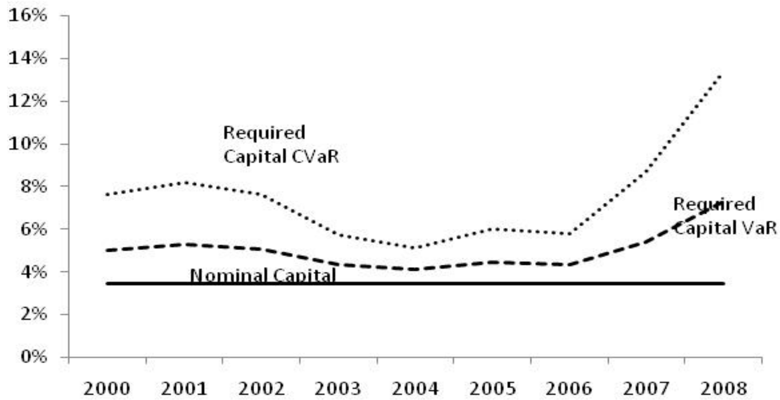


Figure 6. Required capital to cover fluctuations in asset values.

Figure 5 compares nominal capital to real capital, where real capital in this graph is Nominal capital (*K*)–Asset VaR (at 95% confidence level). Figure 6 shows the required capital to cover asset value fluctuations for Swiss banks. Required capital as measured by VaR is nominal capital + VaR, and to cover extreme asset fluctuations is nominal capital + CVaR.

Summary and Conclusions

Four key observations are made from the results. Firstly VaR, CVaR, DD and CPD all follow a similar trend. Risk is moderately high during the early 2000's reducing substantially during the mid 2000's and increasing dramatically during the GFC.

Second, Swiss banks show similar default levels to the Pool. However this is brought about through a combination of lower equity and lower asset value fluctuations as compared to the pools higher equity and higher asset value fluctuations.

Third, default probabilities based on fluctuating asset values are much higher than default probabilities shown by external credit ratings.

Fourth, asset value fluctuations have severely eroded bank equity during the GFC. In real terms capital adequacy is poor, and nominal capital needs a significant boost.

The results of this study provide a strong case for fluctuating asset values to be factored into the determination of appropriate capital levels by banks themselves and/or regulators. Leverage ratios and static capital buffers are certainly a step in the right direction, however the setting of these levels needs to factor in moving asset values. It is of course not practical to have continuously fluctuating capital requirements. However, it is strongly recommended that the required capital adequacy level is based on an assessment over time of real, as opposed to nominal capital. CStdev is recommended as a good method for assessing real capital requirements (as per Figures 5-6), given that it measures tail risk, and extreme circumstances are when banks are most likely to fail.

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