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Economic Capital: An Alternate Copula-Free Approach

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ECONOMIC CAPITAL: AN ALTERNATE COPULA-FREE APPROACH

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Abstract

Economic capital models are getting increasingly complex. An alternate copula-free approach is presented that uses accounting data and an implicit correlation model to simplify economic capital calculations. Model simplification leads to robust and stable models.

A banking case study is used to showcase how the model can be deployed using publicly available accounting data, capital adequacy, leverage ratios and shortfall tools.

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Capital: A First Look

Among the many uses of capital, one use is its ability to send signals to regulators, customers and partners. Models and their usage give an indication of the sophistication and maturity of an organization. Regulators as well as rating agencies assess organizational depth and robustness by evaluating how capital models are used within an organization.

A financial institution's reliance on mature capital modeling can help boards make informed capital allocation decisions. Used judiciously, it allows a bank or an insurance company to price risk properly and compensate risk-taking behavior across products and business lines. Used incorrectly, it leads to an aggressive search for regulatory arbitrage—pushing and testing efficiency frontiers within regulatory capital models.

Regulatory frameworks apply a simpler approach to assessing capital across financial institutions. Within a given region, all banks are measured by the same yardstick—a yardstick that gives more weight to uniformity and standardization than measures of risk that retain stability under extreme conditions. There is a logical reason for that. Regulators, are just as responsible for normal conditions as they are for extreme scenarios. They are responsible for implementation across degrees of sophistication that exist in the banking industry, from small Main Street banks to Wall Street firms. Finally, to support self-regulation and model sophistication, some modeling parameters were allowed to be set on a discretionary basis by a bank's own reporting team.

Since extreme scenarios occur infrequently and we suffer from collective short memory, over time our reporting focus shifts to managing normal scenarios. We add limited sophistication, keeping in view the industry's ability to implement and keep up with modeling expertise. The result is a sprinkling of extreme conditions rather than the ability to survive a truly extreme environment.

From an industry point of view, regulatory reporting is a burden and more often than not leads to public disclosures. Would we really want to share our internal secret sauce and have it misunderstood and shared with our competition? Would we rather spend time focusing on and running our business or educating our regulator so that next year they can come back with more probing and awkward questions? From an industry point of view, there has always been an incentive to minimize the burden and sophistication of regulation. If three words could describe the official industry stance, they would be "Less is more."

1. Economic Capital

As shareholders, partners and customers, some of us are not that interested in regulatory capital beyond reporting requirements. Regulatory frameworks are limited by their desire to include the lowest common denominator. By appearing to be reasonable and fair, they give up on their ability to deal with conditions that by definition are politically incorrect. They are often inflexible, out of date and overly complicated. As a board member of a financial institution, while I am accountable for my banking licenses, my true obligation lies with efficient usage of capital over the long term. That mindset generally doesn't reconcile well within regulatory frameworks.

Regulatory capital is like the speed limit that most drivers will ignore unless they are approaching a radar gun (your quarterly or monthly regulatory reporting cycle). Economic capital is the speed at which you actually drive based on your assessment of road conditions—sometimes above, sometimes below the posted limit. However what is best for the driver may not always be best for people driving or walking around him. The right capital framework finds the line that lies between institutional freedom, flexibility and collective good.

While internal capital models are sometimes an extension of regulatory models used with different parameters, there are variations that take a completely different approach from existing bank regulation. Capital models derived from regulatory approaches suffer from the issues that cannot be fixed by a simple parameter extension.

Here is an initial list of criteria for a standalone economic capital model that does not rely on extending or tweaking regulatory capital models.

- **Accounting reconciliation**. An economic capital model must reconcile with accounting data. An ideal economic capital model should derive results from accounting data.
- **Model correlation**. The best correlation models are implicit rather than explicit. The best possible way of modeling market, credit, operational, interest rate mismatch, legal and reputational risk is identifying a return series that represents these risks in aggregate rather than rebuild a series from individual streams.
- **Simplicity and parameters**. A model must be explainable to senior management and board with as few model parameters as possible.
- **Relevance**. The model output must lead to relevant and actionable intelligence rather than esoteric results that cannot be put into practice.

a. The Appeal of Accounting Data

With the arrival of fair value accounting, mark-to-market disclosures and the Sarbanes-Oxley Act of 2002 (SOX), the quality of accounting data has improved over the last two decades. It is not a perfect proxy but it is represents the closest number we have to a credible, audited series. Accounting data for profit and loss (P&L), capital and balance sheet exposures also incorporates the net interaction between market, credit, operational, legal and interest rate risks. Hedged or unhedged market and rate volatility results now flow through either P&L or shareholders' equity. If you use accounting data, there is no need to build a complicated correlation model that factors in the relationship between business lines. Removing the correlation model simplifies the number of model parameters. That one factor by itself compensates for any perceived shortcomings of using accounting data.

The usage of accounting data in risk modeling is not new. We have a history of calibrating value at risk (VaR) models using P&L generated from the accounting system. What is being proposed is extending that approach to the complete collection of business lines—not just treasury income. The approach is similar to using portfolio model results for a multi-asset investment portfolio VaR calculation, short circuiting the need to use a variance-covariance matrix.

Accounting data is also easily understood by board members and senior management. There is no magical transformation, no exotic black boxes that need to be explained.
But there are also challenges. Accounting focus tends to be short term, generally limited to one year. Economic capital by definition has to have a longer term outlook. Accounting approximations in the area of credit, loan loss reserves, collateral valuation and recoveries have estimation and mark-to-market issues that need to be addressed. After segregating income by business lines, we need an accounting capital allocation model by business line. Segregating P&L by business line is easy; segregating capital for the same lines on a month-to-month basis is a question mark. Having said that, working around these issues is still easier than building a robust correlation model that cuts across business lines, risk types and extreme market conditions.

The model version 1.0

Here is a high level overview of what we want our model to do.

- **Use historical accounting data variations to estimate the probability of regulatory or market-based intervention**. Markets intervene when they taste blood in the water. A market intervention results in a stampede (run) to reduce exposure to the name in question. Regulators intervene when they feel a market intervention will create a domino effect and threaten the stability of financial systems. A market intervention follows the winner-takes-all, last-in, first-out approach. A regulatory intervention tries for an ordered shutdown, exit or takeover.

- **Use core regulatory ratios as input**. While one cannot forecast the order in which interventions occur, the leading event is a name crisis. Analysts forecast the impact of the name crisis on core ratios and the speed with which rating agencies will degrade credit ratings and feed the crisis. Regulatory capital, capital adequacy, liquidity and leverage are four core ratios the model uses to track the probability of intervention.

- **Follow one of two modeling paths**—a P&L (net income) path that tracks the impact of historical P&L changes on common equity as well as capital adequacy, liquidity and leverage or an alternate shareholders' equity path that tracks the impact of historical book equity changes on capital adequacy, liquidity and leverage. For the P&L path to work, a history of large losses is necessary. Without such a history, the model doesn't work. The shareholders' equity path has no such requirements.

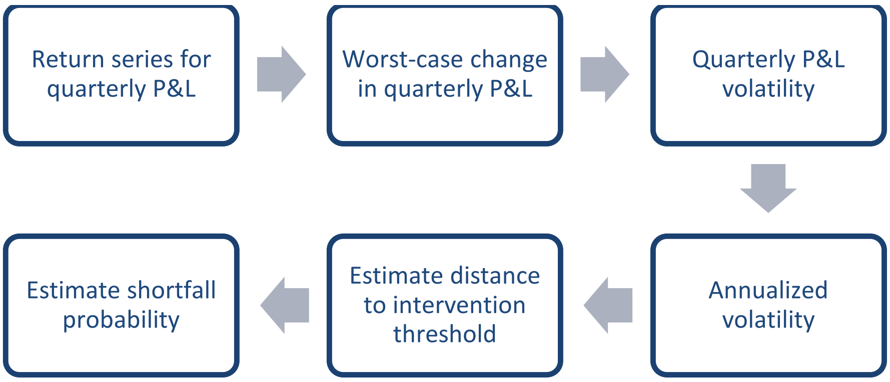


Figure 1. Model process: Using the P&L path

- **Present to and involve the board.** The board sets target intervention probabilities—probabilities that represent acceptable risk of either event for the board. This is done by building a utility curve to show the board capital requirements for each intervention threshold on the curve against existing capital as well as suggested future capital levels.

- **Determine economic capital needs**. The amount of economic capital required is the point where the board picks an acceptable probability threshold for market intervention. This may not necessarily be minimum probability or maximum capital. The amount of required capital associated with the accepted probability is economic capital.

Regulatory capital models work with a value-at-risk tool using a preset confidence level. The economic capital model uses a variation drawn from the same principal but a different family of models called shortfall models. It uses underlying volatility to determine a distance-to-market or regulatory intervention event then converts that distance (measured in terms of volatility) to a probability estimate. The utility curve represents a plot of distances and probabilities used to calibrate and lock the board's risk appetite.

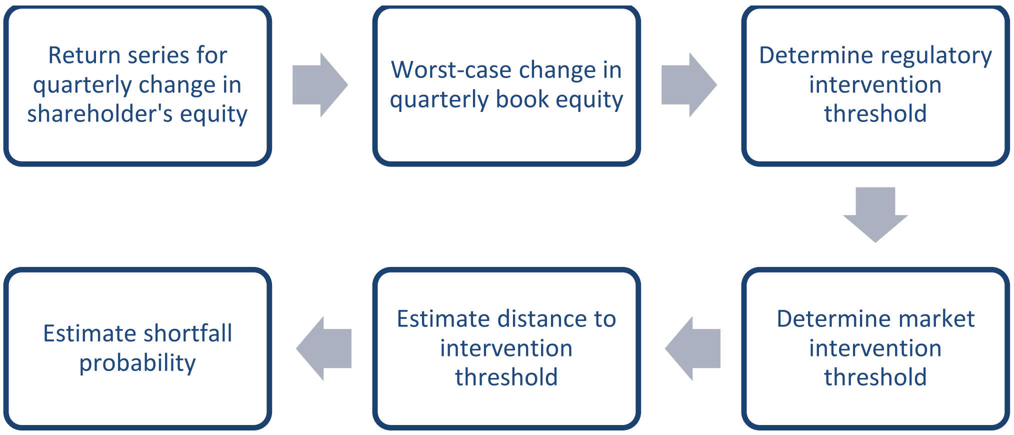
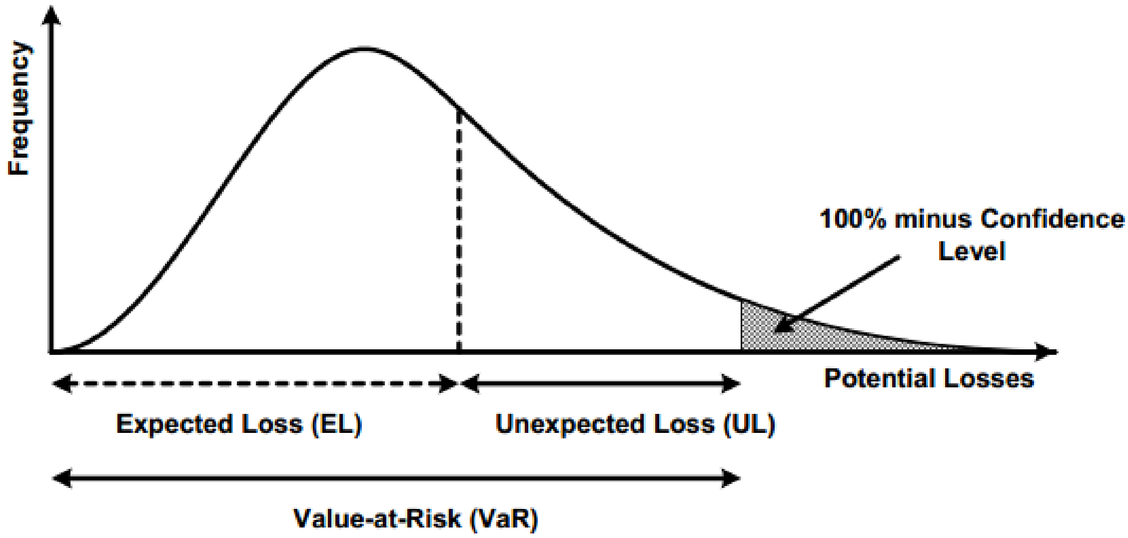


Figure 2. Model process: Using shareholders' equity path

Economic Capital: A Look at Existing Models

Before we move forward with our alternate model, it would be useful to take a look at existing models recommended and used by banking regulators. The comparison would help us make educated decisions when we evaluate the suitability of our alternate accounting-based approach.

Within the regulatory framework, economic capital should compensate for unexpected and unanticipated losses booked when banks and financial institutions are forced to function outside their normal operating environment.



Source: Bank for International Settlement 2005, 3

Figure 3. The difference between expected and unexpected loss

1. Market Risk

To estimate economic capital, the model breaks the return distribution down into two segments: a likely, expected loss and an unlikely, unexpected loss. Unexpected loss is estimated by setting an extremely high threshold (unlikely probability). The difference between unexpected and expected loss serves as an estimate for economic capital. Regulatory guidelines suggest the expected loss figure is determined by the midpoint of the loss distribution.[2] The Bank for International Settlement (BIS) approach assumes that

[2] Within statistics, the mean of a distribution represents the average (expectation), median is the midpoint of the distribution and mode is the most frequent or most common occurrence. For a normal distribution, all three points coincide at a single point but most real life distributions are skewed and have different mean, median and mode values. With the expected loss framework, expected loss is equated to the median of the distribution.

reserves and provisions held on the balance sheet of the bank should adequately cover and compensate for “expected” loss caused by normal operating conditions and economic capital should primarily cover the “unexpected” portion of the loss distribution.

For the model to work, we need a reasonable sized data set and some stability in the return distribution. For instance, if we plan on using the 99.9 percent threshold for unexpected loss, a data set with only 30 data points won’t be effective. The resulting distribution wouldn’t have the granularity we need to answer basic questions focused on how predicted loss numbers would change as we walk up and down the distribution. For example, the monthly return distribution of interest rate changes in a 10-year emerging market sovereign bond does not have sufficient details to build a complete economic capital model because the model is missing definition (details) required to calibrate the model at different probability thresholds (99 percent, 99.9 percent, 99.99 percent). At 99 percent percentile, we need 100 data points for the model to work. For a configuration requiring 99.9 percent or 99.99 percent percentile, we need 1,000 and 10,000 data points respectively.

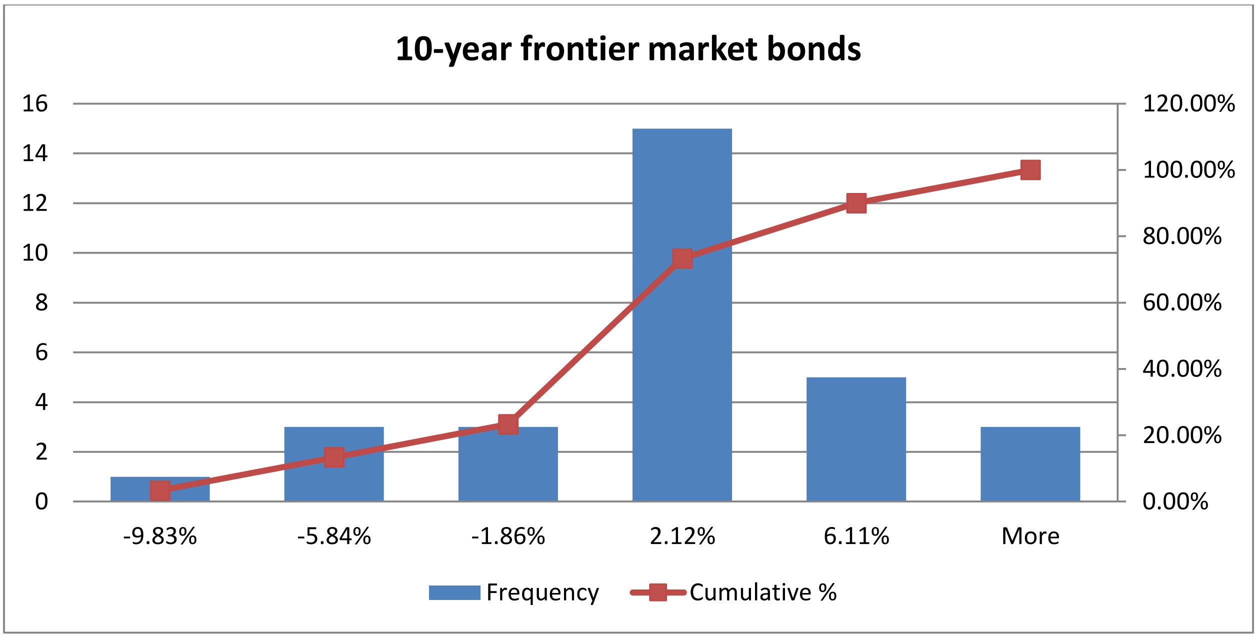


Figure 4. 10-year frontier markets sovereign bond returns distribution

A distribution with 28 years of daily price change data for crude oil price has 7,250 rows of data and can be configured to model capital at the 99.9 percent threshold, possibly higher.

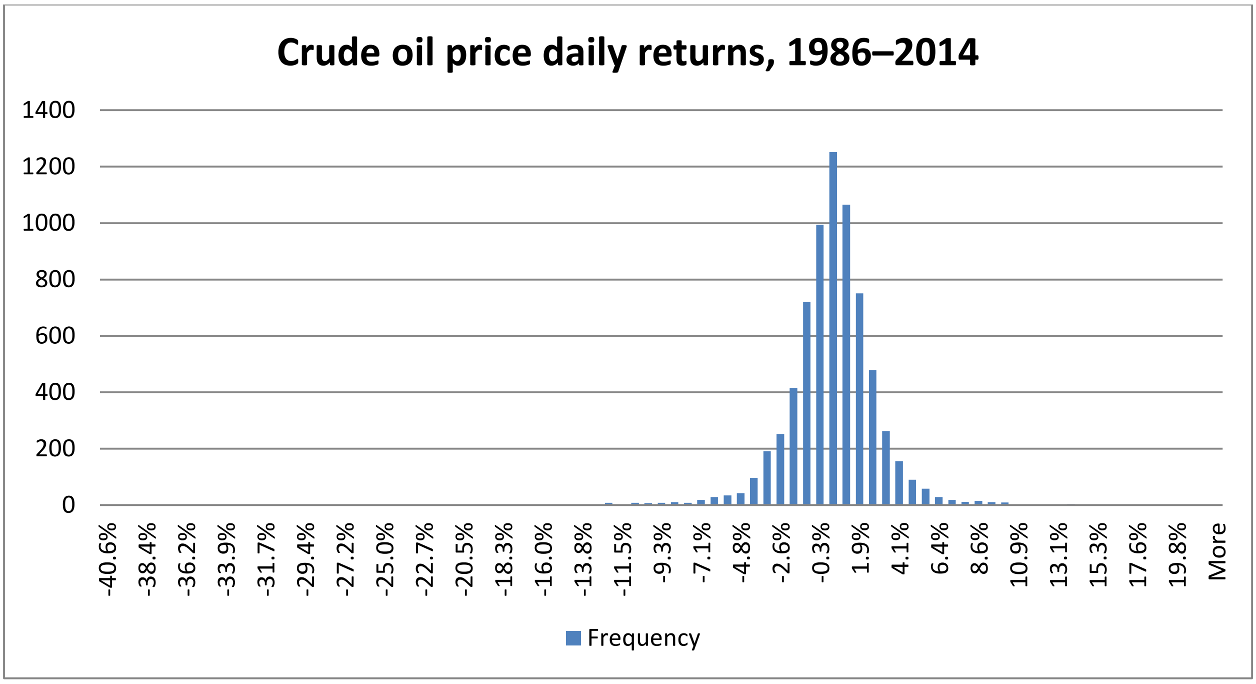


Figure 5. Crude oil (West Texas Intermediate, or WTI) price returns distribution, 1986–2014

But granularity is not the only consideration. Using the oil price distribution as an example, we need to understand how returns are distributed, the shape and form of the distribution, and expectations (mean, median and mode of the return distribution).

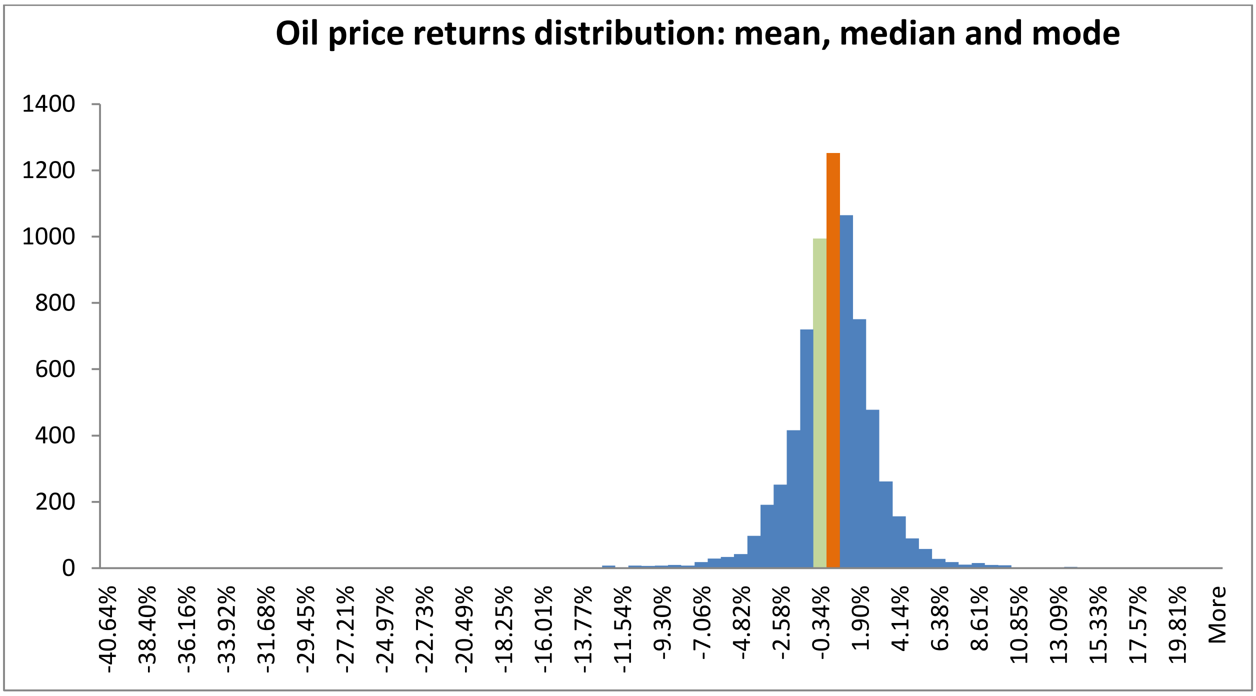


Figure 6. Oil price returns: mean, median and mode

2. Credit Risk

How do we extend this approach for estimating economic capital for credit risk?
The credit risk methodology uses three estimates—probability of default (PD), loss given default (LGD) and exposure at default (EAD) for a given asset class. Once the estimates are available, we also need to factor in correlation between line items in a given asset class as well as across asset classes. That is a significant issue given the number of product types and subtypes available on the credit side and an equally impressive list available on the investment side. Making them all work together on an unexpected loss (UL) calculation for an economic capital model is an awkward task.

a. Calculating Unexpected Loss: A Simplified Case Study

Our starting point for estimating expected loss (EL) is the following equation:

$$EL = PD(\%) * LGD(\%) * EAD(\$)$$

Where:
EL = Expected loss
PD = Probability of default
LGD = Loss given default
EAD = Exposure at default

Let us take a look at each of these components individually.

b. Probability of Default (PD)

PD is the probability that a default will occur on a credit obligation by a client leading to partial or total loss. Probability of default estimation models use a combination of behavioral data (past payment trends and history), financial information (leading indicators based on financial ratios) and subjective information (auditor profile and market feedback) to estimate PDs. Rating agencies use slightly different models to estimate PDs for a given rating class. For instance, the original Standard & Poor model bases credit ratings on an internal assessment of default by a given name:

S&P Ratings	Likelihood of discharge of obligation = (1–PD)
AAA	99.98%
AA	99.95%
A	99.87%
BBB	99.32%
BB	97.60%
B	88.36%

c. Loss Given Default (LGD)

LGD is the conditional expectation of loss given that default has already occurred. LGD estimates vary depending on the underlying transaction, committed collateral, security and claim type of a loan. LGD could also be expressed as (1–RR) where RR stands for recovery rate. LGD also becomes important when in addition to rating obligors, we also rate facilities. Also see Altman (2009).

d. Exposure at Default (EAD)

EAD is an estimate that measures the exposure of a counterparty at the time of default. Imagine a working capital, overdraft or running finance line originally approved for $1 million. At the point that default occurs, would this line be fully drawn, partially drawn or completely undrawn? A funded line of credit or commitment is relatively straight forward, but unfunded and contingent exposures are a little more complicated.

A forward contract on a foreign currency comes with local currency exposure that changes with changes in exchange rates. As rates go up and down, the replacement cost on the contract if a default occurs also moves. Multileg interest rates and cross currency swaps are more complex because we now begin to deal with multiple benchmark rates at multiple points in the future. For such exposure, a simple **replacement cost** estimate at a given point in time is not sufficient; we need to evaluate the **worst-case exposure across the life of the transaction** (aka, potential future exposure). See Jimenez, Lopez and Saurina (2009).

When we put all of these considerations together, the EAD value is modeled as under:

- For normal conventional lending products:

$$EAD = Drawn\ portion\ of\ the\ line + LEQ * Undrawn\ amount$$

Where:

LEQ = Loan equivalent amount

- For derivative, unfunded and contingent exposure:

$$EAD = \alpha * (RC + PFE)$$

Where:

$\alpha = 1.4$

RC = Replacement cost

PFE = Potential future exposure

e. Expected Loss (EL), Unexpected Loss (UL) for Derivative Exposure

In our sample UL case study, we will use publicly available financial statement data for a large bulge bracket investment bank to estimate expected loss, unexpected loss and capital requirements using the approaches discussed above. We will make a number of simplifying assumptions and use shortcuts to improve readability.

We start with notional exposure (expressed in US$ '000) to derivative contract counterparties under the following categories.

Assets	Notional Exposure (US$ '000)
Receivables from Interbank counterparties	24,000
Due from customers on derivative contracts	89,000
Derivative contracts on financial instruments	333,000
Total Notional Exposure	446,000

Figure 7. Notional exposures

f. Unexpected Loss Case Study: EAD and EL Calculations

Using the above exposures and the preceding model for estimating EAD for derivative contracts, we end up with the following values for EAD.

Assets	Replacement Cost	Potential Future Exposure	EAD (%)
Receivables from Interbank counterparties	20%	0%	28%
Due from customers on derivative contracts	10%	20%	42%
Derivative contracts on financial instruments	5%	10%	21%

Figure 8. Estimating EAD

Using our EAD estimate from above, we also add probability of default, loss given default and notional exposure in dollar terms to estimate the expected loss figures for each of the above mentioned line items.

Assets	PD (%)	LGD (%)	EAD (%)	Notional Exposure (US$)	EAD ($)	Expected Loss (EL)
Receivables from Interbank counterparties	**2%**	**80%**	**28%**	**24,000**	**6,720**	**108**
Due from customers on derivative contracts	**4%**	**40%**	**42%**	**89,000**	**37,380**	**598**
Derivative contracts on financial instruments	**3%**	**25%**	**21%**	**333,000**	**69,930**	**524**

Figure 9: Calculating expected loss

The EL amount is calculated using the expected loss equation:

$$Total\ EL = \sum_{i}^{n} PD_i * LGD_i * EAD_i$$

g. Unexpected Loss Case Study: Calculating UL Using the Short-Form Approach

The equation for the calculation of UL needs some work. See Antwi et al. (2013) on the more detailed mathematical derivation. For a single credit exposure, unexpected loss UL is given by:

$$\text{UL}=\sqrt{\begin{aligned}&PD^2EAD^2\sigma_{LGD}{}^2+EAD^2LGD^2\sigma_{PD}{}^2+LGD^2PD^2\sigma_{EAD}{}^2+PD^2\sigma_{EAD}{}^2\sigma_{LGD}{}^2\\&+EAD^2\sigma_{LGD}{}^2\sigma_{PD}{}^2+LGD^2\sigma_{PD}{}^2\sigma_{EAD}{}^2+\sigma_{PD}{}^2\sigma_{EAD}{}^2\sigma_{LGD}{}^2\end{aligned}}$$

PD = Probability of default

EAD = Exposure at time of default

LGD = Loss given default

Within the above equation, EAD is deterministic (known) and hence has a variance of zero. That reduces the equation from seven terms to three.

$$\text{UL}=\sqrt{\begin{aligned}&PD^2EAD^2\sigma_{LGD}{}^2+EAD^2LGD^2\sigma_{PD}{}^2+LGD^2PD^2\sigma_{EAD}{}^2+PD^2\sigma_{EAD}{}^2\sigma_{LGD}{}^2\\&+EAD^2\sigma_{LGD}{}^2\sigma_{PD}{}^2+LGD^2\sigma_{PD}{}^2\sigma_{EAD}{}^2+\sigma_{PD}{}^2\sigma_{EAD}{}^2\sigma_{LGD}{}^2\end{aligned}}$$

$$\text{UL}=\sqrt{\begin{aligned}&PD^2EAD^2\sigma_{LGD}{}^2+EAD^2LGD^2\sigma_{PD}{}^2+\cancel{LGD^2PD^2\sigma_{EAD}{}^2}+\cancel{PD^2\sigma_{EAD}{}^2\sigma_{LGD}{}^2}\\&+EAD^2\sigma_{LGD}{}^2\sigma_{PD}{}^2+\cancel{LGD^2\sigma_{PD}{}^2\sigma_{EAD}{}^2}+\cancel{\sigma_{PD}{}^2\sigma_{EAD}{}^2\sigma_{LGD}{}^2}\end{aligned}}$$

We take EAD out of square root, ignore the smaller terms and are left with:

$$UL = EAD * \sqrt{[(PD^2 * \sigma^2{}_{LGD}) + (LGD^2 * \sigma^2{}_{PD})]}$$

Where PD is assumed to follow a Bernoulli distribution and LGD follows a beta distribution and hence leads to:

$$\sigma^2{}_{\mathrm{LGD}} = \text{Variance of loss given default} = (\mathrm{LGD})(1 - \mathrm{LGD})/4$$

$$\sigma^2{}_{\mathrm{PD}} = \text{Variance of probability of default} = (\mathrm{PD})(1 - \mathrm{PD})$$

Putting all of the above to work together gives us our first estimate on unexpected loss using the short-form approach.

Assets	EAD	PD	LGD	Variance PD	Variance LGD	UL - Shortform (% of EAD)	UL ($)
Receivables from Interbank counterparties	28%	5%	80%	5%	4%	17%	1,174
Due from customers on derivative contracts	42%	4%	40%	4%	6%	8%	2,953
Derivative contracts on financial instruments	21%	7%	25%	7%	5%	7%	4,585

Figure 10. Calculating unexpected loss using the short-form approach

h. Unexpected Loss Case Study: Calculating Unexpected Loss Using BIS Method

The BIS standard method for capital charge calculation is a little different. Ignoring the impact of correlation, the BIS approach essentially calculates unexpected loss at 99.9 percent threshold, subtracts the expected loss given by multiplying **PD x LGD x EAD** and uses the difference as its estimate for capital requirement. There are a number of adjustments made in the formula for maturity and correlations but we will ignore these for the purpose of simplifying presentation in our case study.

The full form of the capital charge equation follows. See Bank for International Settlements (2005) for a more detailed treatment.

Standard normal distribution (N) applied to threshold and conservative value of systematic factor

Inverse of the standard normal distribution (G) applied to PD to derive default threshold

Inverse of the standard normal distribution (G) applied to confidence level to derive conservative value of systematic factor

$$\text{Capital requirement (K)} = [LGD * N[(1 - R)^{-0.5} * G(PD) + (R / (1 - R))^{0.5} * G(0.999)] - PD * LGD] * (1 - 1.5 \times b(PD))^{-1} \times (1 + (M - 2.5) * b(PD))$$

Color coding the above diagram shows the relevant sections of the equation:

a) The sections of the equation underlined in green deal with the correlation adjustment within the asset class.
b) The grey underlined components calculated the EL and UL at 99.9 percent.
c) The red underlined section is the EL adjustment from the UL result.
d) The yellow highlighted section is the maturity adjustment.

Standard normal distribution (N) applied to threshold and conservative value of systematic factor

Inverse of the standard normal distribution (G) applied to PD to derive default threshold

Inverse of the standard normal distribution (G) applied to confidence level to derive conservative value of systematic factor

$$\text{Capital requirement (K)} = [LGD * N[\underline{(1 - R)^{-0.5}} * \underline{G(PD)} + \underline{(R / (1 - R))^{0.5}} * \underline{G(0.999)}] \underline{- PD * LGD}] * (1 - 1.5 \times b(PD))^{-1} \times (1 + (M - 2.5) * b(PD))$$

Assuming zero correlation and plugging in our EAD, LGD and PD values in the above equation, we get the following model implementation in Excel.

E	F	G	H	I	J	K	L
EAD	PD	LGD	Variance PD	Variance LGD	UL - Shortform (% of EAD)	UL ($)	BIS - UL (%)
28%	5%	80%	5%	4%	17%	1,174	21%
42%	4%	40%	4%	6%	8%	2,953	15%
21%	7%	=(NORMSDIST(NORMSINV(F30)+NORMSINV(E25)))*G30*E30					

Figure 11. Unexpected loss using BIS method

We take the z-score for our current estimate of PD, add the 99.9 percent z-score to it, add both numbers to calculate the revised worst-case PD and multiply the result with EAD and LGD estimates for that line item.

	99.90%							
Assets	EAD	PD	LGD	Variance PD	Variance LGD	UL - Shortform (% of EAD)	UL ($)	BIS - UL (%)
Receivables from Interbank counterparties	28%	5%	80%	5%	4%	17%	1,174	21%
Due from customers on derivative contracts	42%	4%	40%	4%	6%	8%	2,953	15%
Derivative contracts on financial instruments	21%	7%	=(NORMSDIST(NORMSINV(F30)+NORMSINV(E25)))*G30*E30					
		© FinanceTrainingCourse.com					8,711	

Figure 12. Unexpected loss using BIS method by line item

Zooming out and repeating it across the three exposures we have been following in this case study, we get:

Assets	EAD	EL	UL - Shortform	Economic Capital (A)	BIS - UL	Economic Capital (B)
Receivables from Interbank counterparties	28%	108	1,174	1,066	1,394	1,286
Due from customers on derivative contracts	42%	598	2,953	2,355	5,713	5,115
Derivative contracts on financial instruments	21%	524	4,585	4,060	3,476	2,951
Grand Total		1,230	8,711	7,481	10,583	9,353
	© FinanceTrainingCourse.com			1.68%	UL % of Notional	2.10%
				6.56%	UL % of EAD	8.20%

Figure 13: Calculating economic capital

BIS UL in column (6) is the BIS estimate for unexpected loss. Economic capital (B) in column (7) is the adjusted capital charge after deducting the expected loss calculated in column (2). The short-form approach understates unexpected loss for the data set used in the case study. The BIS approach leads to higher UL as well as higher capital charge estimates in our simplified model. Plugging in correlation estimates should help bring the numbers closer together because we do use them in the short-form approach but ignore them in our contrived BIS example.

Remember our original disclosure. This is a simplified presentation assuming zero correlation and using a model for a single credit exposure. When you extend UL for multiple exposures or across multiple asset classes, the equation becomes quite intimidating and daunting.

$$Total\ UL = \sqrt{{UL_1}^2 + {UL_2}^2 + \cdots + {UL_n}^2 + 2\rho_{1,2}UL_1UL._2 + 2\rho_{1,3}.UL_1.UL_3 + \cdots + 2\rho_{n,n}.UL_n.UL_n}$$

Case Study: An Alternate Approach

Now that we have taken a high level look at the current practice, the best way to illustrate our shortfall economic capital model is to walk through a banking case study. Here is our plan.

We look at five financial institutions: Goldman Sachs Group Inc., Citibank, JPMorgan Chase & Co., Wells Fargo & Co. and Barclays Bank PLC. Citibank, JPMorgan, Wells Fargo and Barclays are wholesale banks with a strong retail and commercial banking franchise. Goldman Sachs is a leading investment bank with as much exposure internationally as the other four but the core business for Goldman Sachs is not retail or commercial banking. The first four are U.S. based. Barclays is the only British/European bank on the list.

While JPMorgan and Wells Fargo did well during and after the financial crisis, others have not. Citibank and Barclays have been in and out of trouble and Goldman Sachs had a narrow brush with mortality during the financial crisis. JPMorgan also experienced a few hiccups with the London Whale and foreign exchange rate-fixing scandal.

How do Goldman Sachs, Citibank, JPMorgan Chase, Wells Fargo and Barclays Bank differ from each other when it comes to economic capital requirements? Can the same economic capital algorithm work for all five banks? More importantly, can we build a model by just using publicly disclosed financial information without getting insider-level access at the business-line level?

Our initial perception based on raw regulatory capital requirements suggest that everything is well under control. Citibank and Barclays could potentially do with a bit more capital but Goldman Sachs, JPMorgan and Wells Fargo are apparently running a tight ship. In terms of strength of capital stock, we would rate JPMorgan the highest, followed by Wells Fargo and then Goldman Sachs.

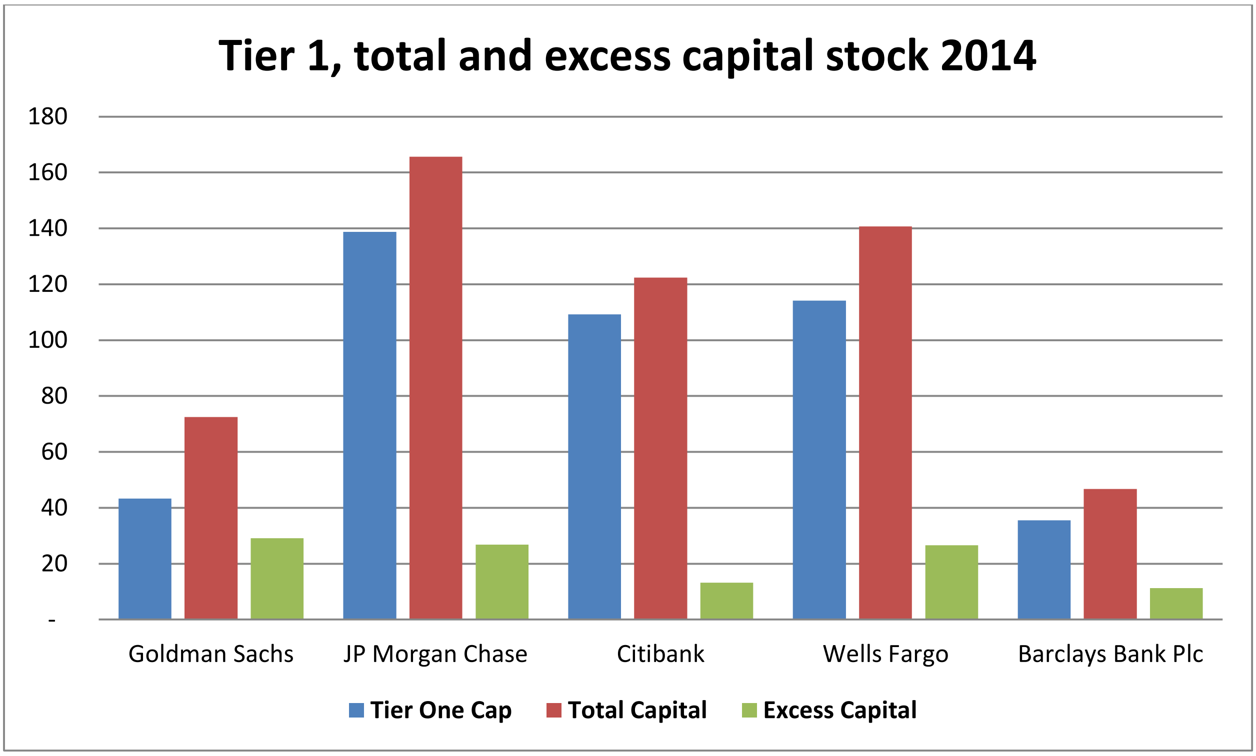


Figure 14. Tier 1, total and excess capital stock, 2014

But are these perceptions correct? Would this order change when we switch from regulatory capital to economic capital?

1. Data Set and Methodology

We use data from publicly available quarterly financial statements for our five banks starting with financial year 2002 and ending with financial year 2014. For Barclays, financial information was available on a semi-annual basis and the Barclays model has been adjusted to reflect that gap.

The 2002–13 data set is available at ycharts.com. Dec. 31, 2013, and first and second quarter 2014 information has been sourced directly from investor relations sections of each bank's website. We use the return series methodology (see subsection (a) of this section) to calculate quarterly returns for each bank. The return series is plotted using a histogram to get a sense for the underlying distribution and is also used to estimate volatility within the series.

We begin with the shareholders' equity data series but we will also take a look at the net income series before we wrap up our analysis.

2. Method One: Economic Capital Using Changes in Shareholders’ Equity

Our Method One for estimating economic capital uses raw data to come up with an initial estimate of economic capital. In later approaches, we will use many of the same themes with slightly different variations.

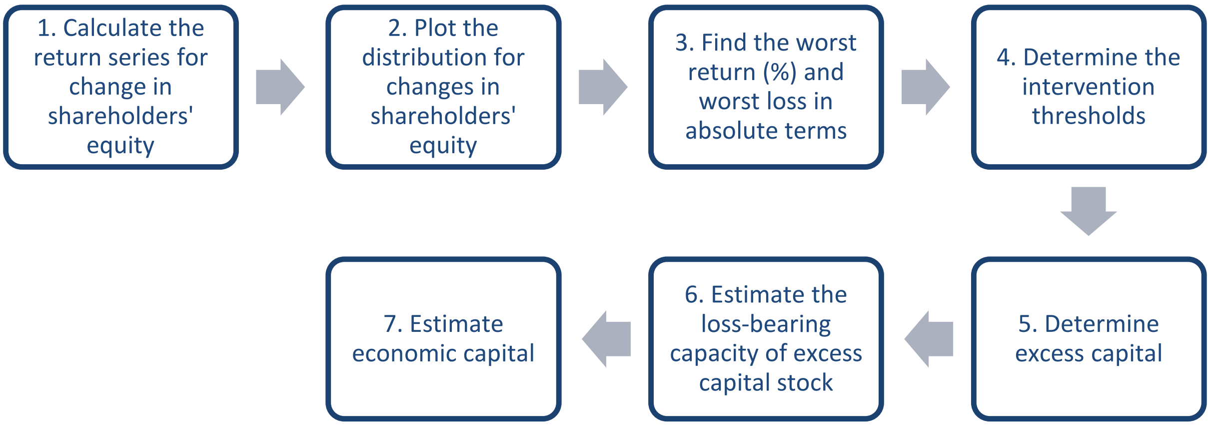


Figure 15. Model process: Method One

Step 1. Calculate the return series for change in shareholders’ equity

Once we have collated the data from our data source, the first step is to calculate the return series for the five banks from 2002 to 2014. We are measuring the rate of change in shareholders’ equity from one quarter to the next quarter. Here are the results for the five banks based on the data set from 2002 to 2014. Barclays data as discussed is on a semi-annual basis. All other banks are on a quarterly basis.

	Goldman Sachs		JP Morgan		Citi bank		Wells Fargo	
Quarter / Year	Shareholder equity (Billions USD)	Return series	Shareholder equity (Billions USD)	Return series	Shareholder equity (Billions USD)	Return series	Shareholder equity (Billions USD)	Return series
1st Quarter of 2002	18.50		41.13		83.64		28.28	
2nd Quarter of 2002	18.86	1.9%	42.74	3.8%	85.72	2.5%	29.47	4.1%
3rd Quarter of 2002	18.84	-0.1%	43.44	1.6%	80.77	-5.9%	30.02	1.8%
4th Quarter of 2002	19.00	0.8%	42.31	-2.6%	86.72	7.1%	30.07	0.2%
1st Quarter of 2003	19.51	2.6%	43.08	1.8%	87.34	0.7%	30.72	2.1%
2nd Quarter of 2003	20.04	2.7%	44.82	4.0%	93.3	6.6%	32.22	4.8%
3rd Quarter of 2003	20.44	2.0%	44.96	0.3%	95.26	2.1%	32.32	0.3%
4th Quarter of 2003	21.63	5.7%	46.15	2.6%	98.01	2.8%	34.26	5.8%
1st Quarter of 2004	22.24	2.8%	48.10	4.1%	101.88	3.9%	34.99	2.1%
2nd Quarter of 2004	23.15	4.0%	45.94	-4.6%	98.31	-3.6%	35.09	0.3%
3rd Quarter of 2004	23.51	1.5%	105.85	83.5%	103.37	5.0%	36.36	3.6%
4th Quarter of 2004	25.08	6.5%	105.65	-0.2%	109.29	5.6%	37.6	3.4%
1st Quarter of 2005	26.08	3.9%	105.34	-0.3%	110.54	1.1%	37.94	0.9%
2nd Quarter of 2005	26.40	1.2%	105.38	0.0%	113.04	2.2%	38.82	2.3%
3rd Quarter of 2005	26.61	0.8%	106.14	0.7%	111.84	-1.1%	39.45	1.6%
4th Quarter of 2005	28.00	5.1%	107.21	1.0%	112.54	0.6%	40.34	2.2%
1st Quarter of 2006	28.92	3.2%	108.34	1.0%	114.42	1.7%	41.33	2.4%
2nd Quarter of 2006	31.80	9.5%	110.68	2.1%	115.43	0.9%	41.35	0.0%
3rd Quarter of 2006	33.49	5.2%	113.56	2.6%	117.86	2.1%	44.4	7.1%

Figure 16. Rate of change in shareholders' equity

Step 2. Plot the distribution for changes in shareholders' equity

Citibank and Barclays stand out in terms of the breadth of their distribution. Compared to Goldman Sachs, Wells Fargo and JPMorgan, the distance between the worst-case change and the best-case change is the lowest in case of Citibank as well as Barclays.

The probability of a negative change is also highest for Citibank and Barclays compared to Goldman Sachs, Wells Fargo and JPMorgan. Interestingly enough in terms of distribution, Barclays is centered around the highest median change of 13 percent. The other four are all lower than 13 percent.

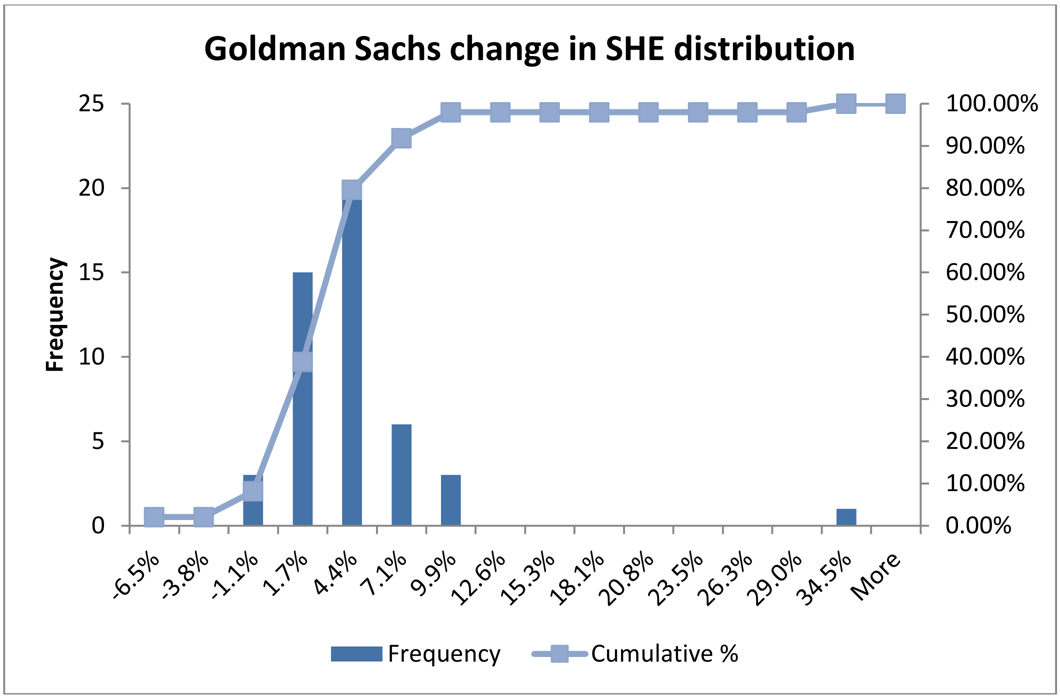


Figure 17. Distribution of rates of change in shareholders' equity, Goldman Sachs

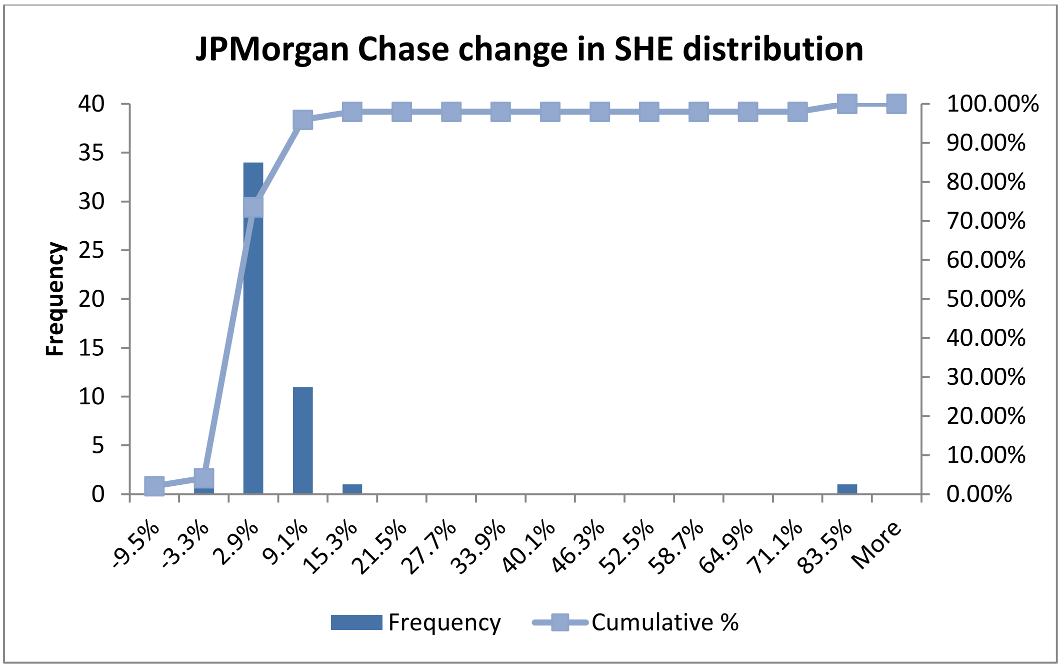


Figure 18. Distribution of rates of change in shareholders' equity, JPMorgan Chase

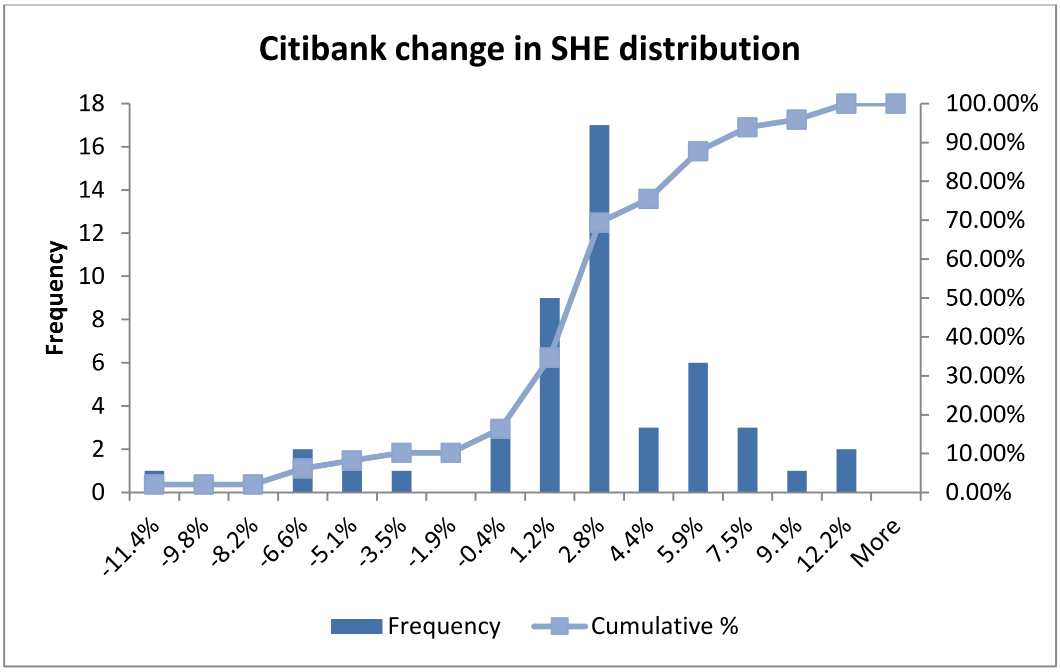


Figure 19. Distribution of rates of change in shareholders' equity, Citibank

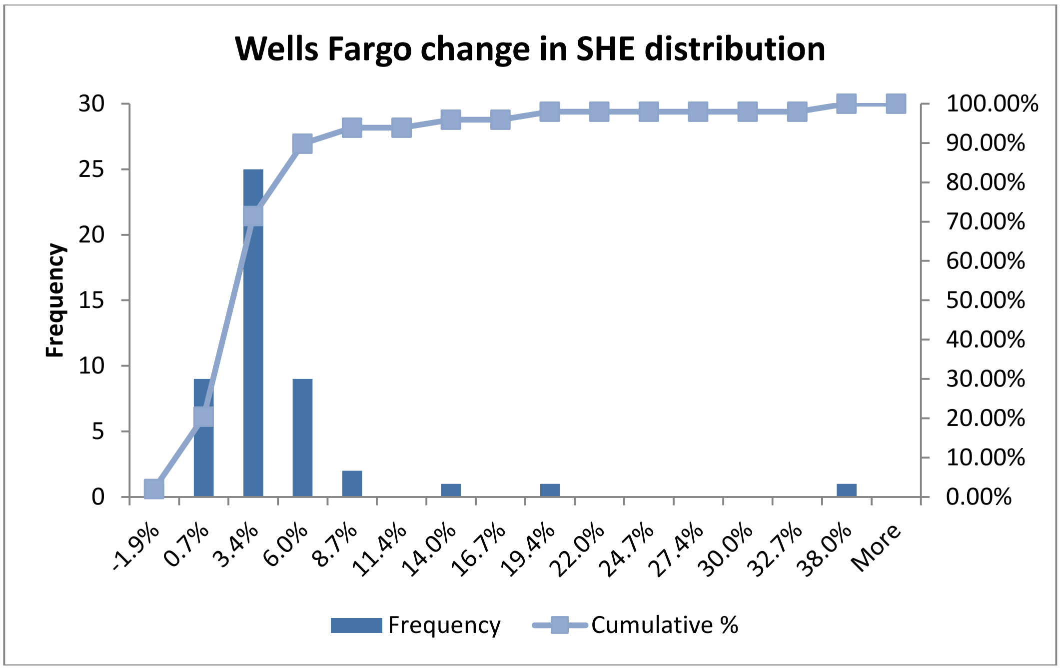


Figure 20. Distribution of rates of change in shareholders' equity, Wells Fargo

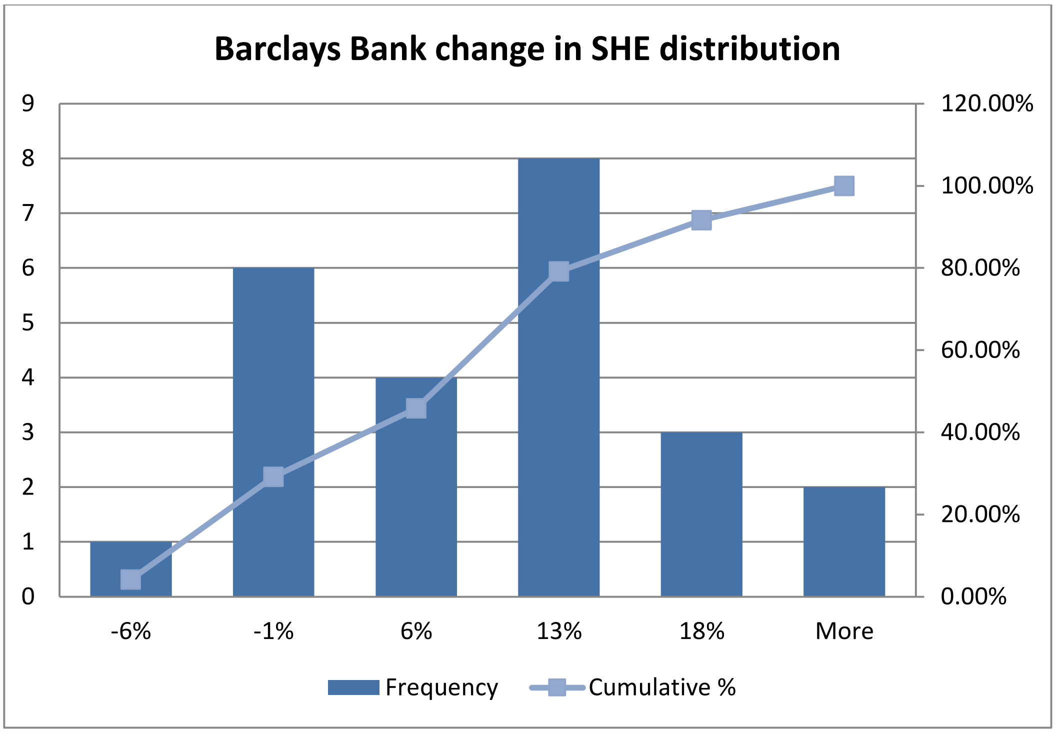


Figure 21. Distribution of rates of change in shareholders' equity, Barclays Bank

Step 3. Find the worst return (percentage terms) and worst loss in absolute terms

The changes in shareholders' equity histogram series above gives us the worst-case change (in percentage terms) for each of our banks. We apply the percentage change on the most recent shareholders' equity value to estimate the absolute worst-case change in dollar terms.

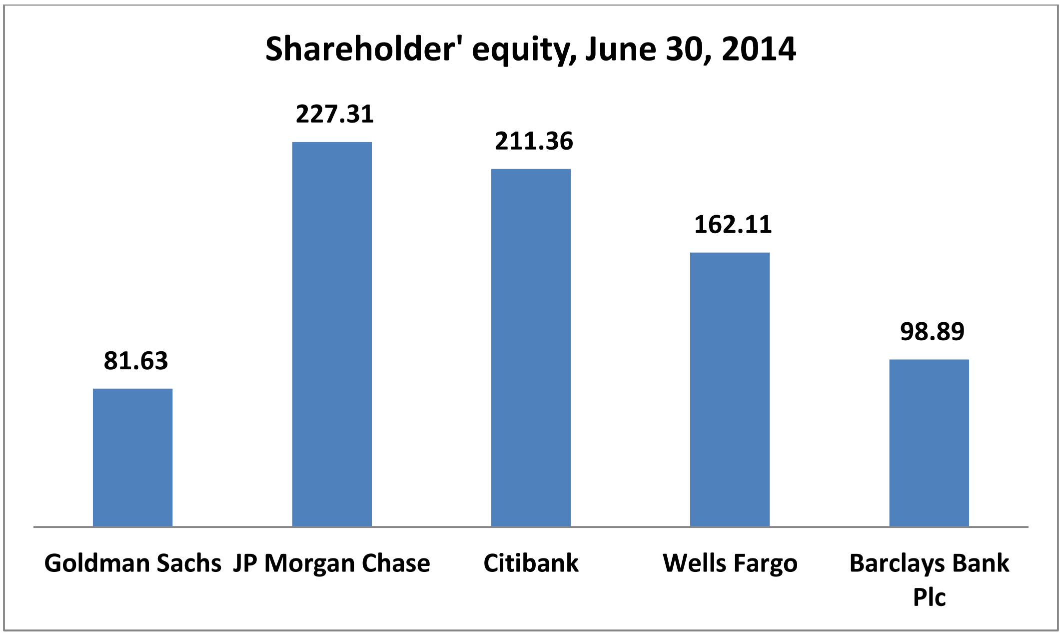


Figure 22. Shareholders' equity as of June 30, 2014

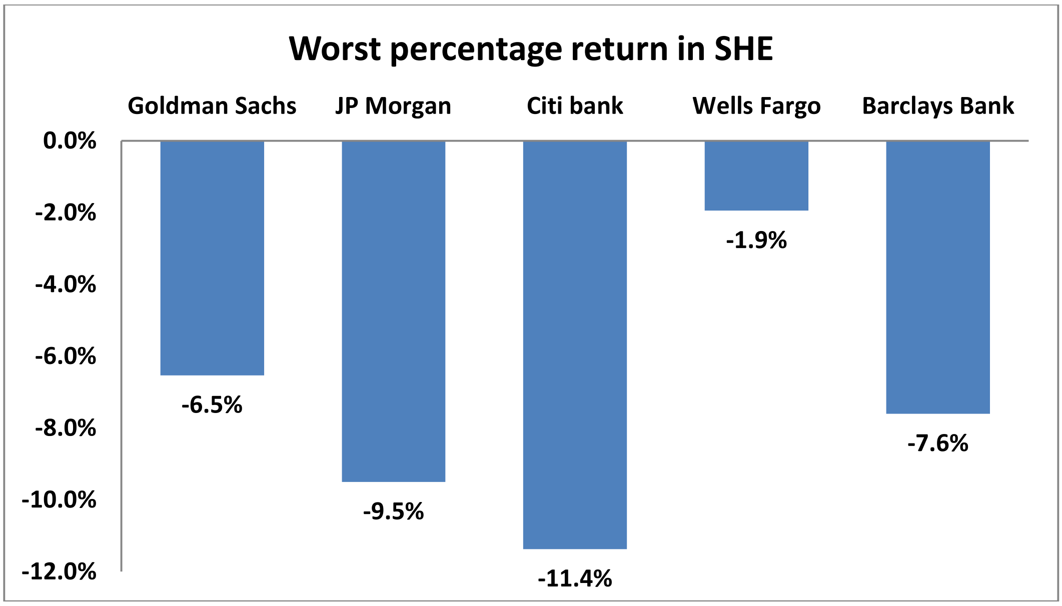


Figure 23: Worst-case change (%) in shareholders' equity

There are two sets of worst-case loss figures. The first uses the last full year results shareholders' equity figures (as of Dec. 31, 2013).

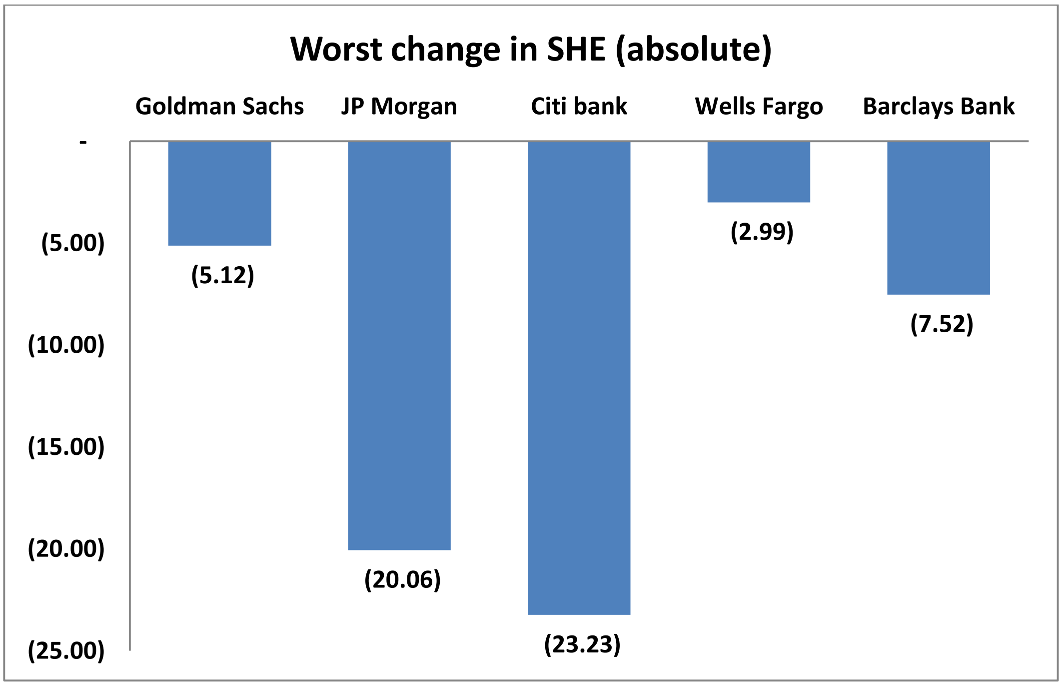


Figure 24: Worst-case change ($) in shareholders' equity, based on Dec. 31, 2013

The second set of numbers uses the most recent quarter (June 30, 2014) figures to estimate the worst-case loss.

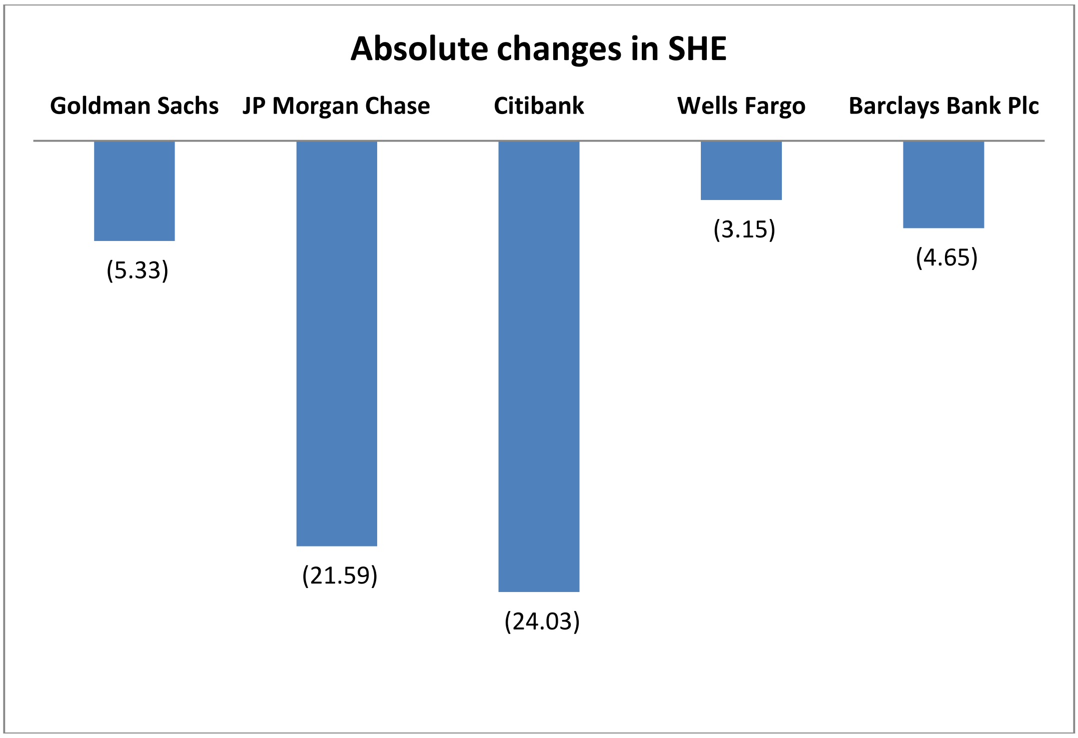


Figure 25: Worst-case change ($) in shareholders' equity, based on June 30, 2014

Step 4. Determine the intervention thresholds

The best intervention models assume that markets and regulators will act before capital is fully depleted. Ideally, at the first hint of trouble, the threat of market or regulatory intervention should make a bank board take corrective actions. Sometimes this implies painful decisions that may be contested but are still better than a complete loss of control. From a modeling point of view, this means we do not have the luxury to see our stock of capital reduce all the way down to zero before external counterparties take notice of our difficulties.

For the purpose of the current exercise, we set the intervention threshold at some minimum capital adequacy requirement. This capital adequacy requirement would be the greater of what the market and the regulator believe a bank should maintain to retain the ability to participate as a counterparty within the interbank market.

For the purpose of our analysis, this threshold has been set at 10 percent.[3] When a bank falls below the 10 percent threshold, model expectation is that either the regulator or market forces will react. An unexpected loss, a large regulatory penalty, a crisis of

[3] For guidelines and commentary on additional Tier 1 capital and total loss absorption capacity, see Financial Stability Board (2014), Board of Governors of the Federal Reserve System (2015) and Bank for International Settlements (2015).

confidence, a run on liquidity, a change in leadership and the loss of a key investor are all triggers that may lead to a change of fortunes and an expected shortfall.

Step 5. Determine excess capital

The stock of excess capital is simply the difference between core capital and regulatory capital requirements. This is the amount that acts as a buffer for future losses.

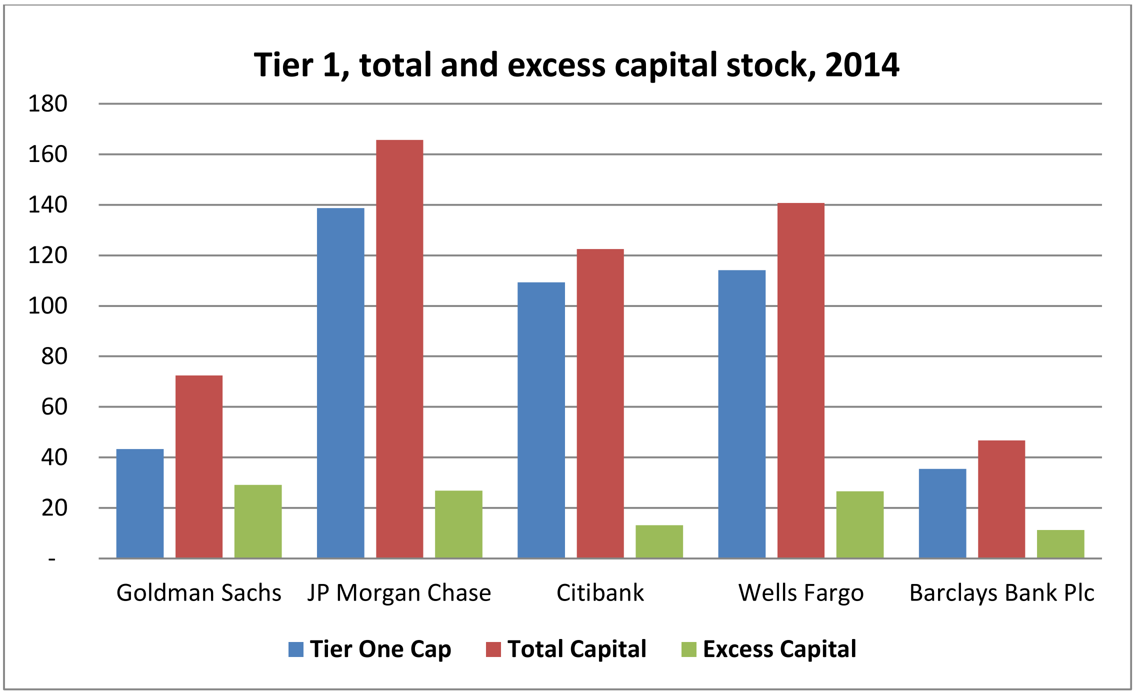


Figure 26. Tier 1, total and excess capital stock, 2014

The question we want to ask is what is the quantum this buffer can bear and protect against? What is the likelihood that a series of events may ultimately lead to claims higher than the calculated excess capital amount.

Step 6. Estimate the loss-bearing capacity of excess capital stock

Turns of protection is simply excess capital stock divided by the worst-case change in shareholders' equity. The odds of a worst-case turn are 1/49 or just over 2 percent for the first four banks. For Barclays, the number is 4 percent because we only had half the data points.

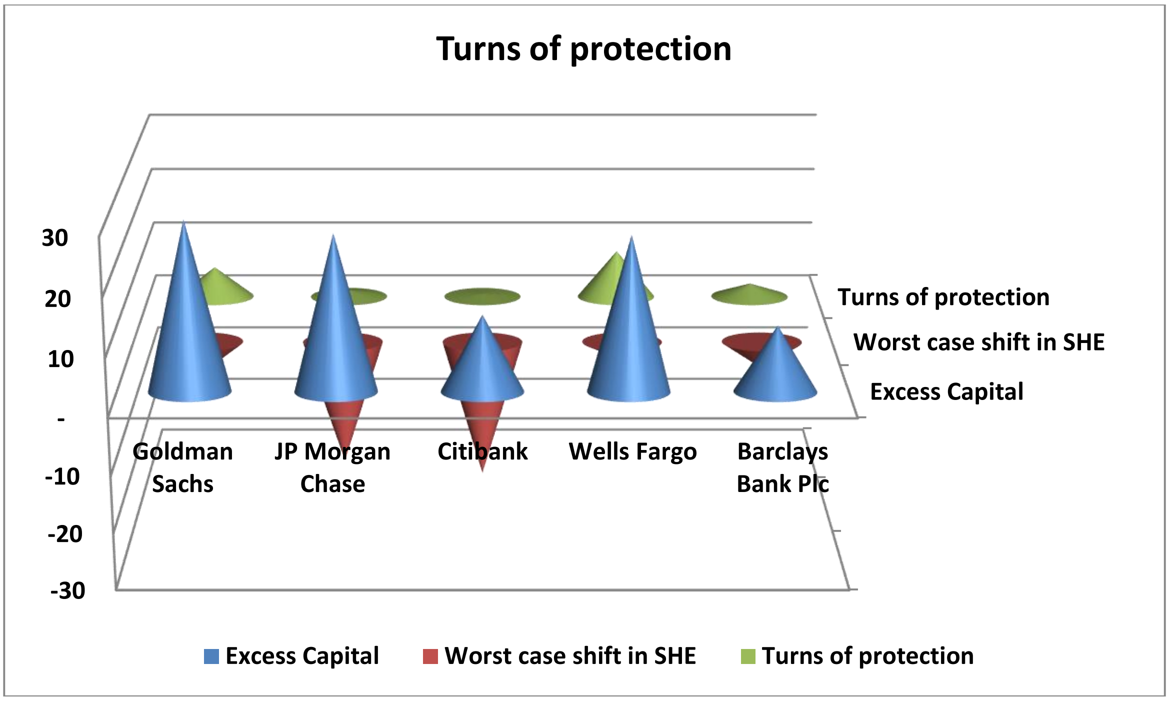


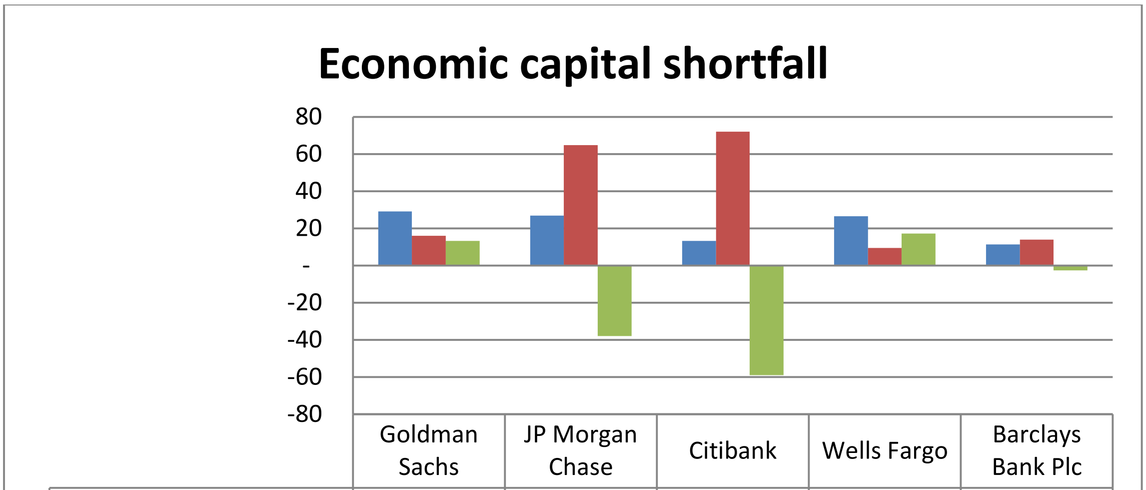
Figure 27. Turns of protection

Step 7. Estimate economic capital

Within the current data set, the probability of a single turn loss equivalent to the worst-case historical loss is just over 2 percent. This is true for the first four banks because the worst-case loss represents one loss in 49 data points. For Barclays Bank, the worst-case loss represents one in 24 data points and the probability doubles to 4.08 percent.

Let's assume that our board decides they are only comfortable when the bank in question has sufficient buffer to withstand not one but three such consecutive shocks. If a bank's reserves of capital can survive three such shocks, then the bank is safe and anything beyond that amount is excess economic capital.

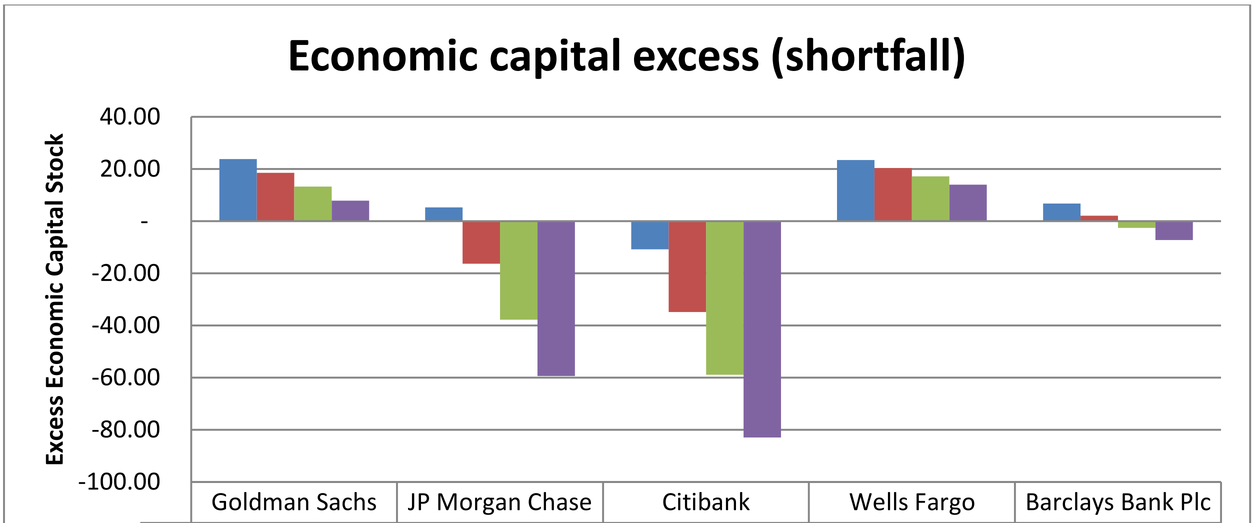
This implies that our estimate for additional economic capital is the difference between regulatory capital and the stock required to survive three shocks.



	Goldman Sachs	JP Morgan Chase	Citibank	Wells Fargo	Barclays Bank Plc
Excess regulatory capital	29	27	13	27	11
Required buffer	15.99	64.77	72.09	9.46	13.94
Excess Economic Capital	13.16	-37.89	-58.91	17.13	-2.62

Figure 28. Economic capital shortfall to survive three shocks

How would these numbers change if we moved the threshold to a single turn or four worst-case loss turns? How do the five banks fare in terms of their stock of economic capital? Which one is the most well capitalized? Which one is worst capitalized off the lot?



	Goldman Sachs	JP Morgan Chase	Citibank	Wells Fargo	Barclays Bank Plc
1	23.82	5.29	-10.85	23.43	6.67
2	18.49	-16.30	-34.88	20.28	2.03
3	13.16	-37.89	-58.91	17.13	-2.62
4	7.83	-59.48	-82.94	13.97	-7.27

Figure 29. Economic capital shortfall, single to quadruple shock

a. Issues With Method One

The primary issue with our Method One for economic capital is it rigidity in calculating probability intervention. While we have a 2 percent probability of intervention for the first four and a 4 percent for Barclays, what if we need to evaluate capital stock at 10 percent or 5 percent?

Here is the problem. Our ability to complete this calculation is dependent on the granularity of the underlying distribution. The distribution differs for each bank. While we could answer this question for Goldman Sachs, JPMorgan, Citibank and Barclays, we won't be able to do the same for Wells Fargo since we don't have enough data points for Wells Fargo. And if we care to calculate the same numbers at a 20 percent threshold, we won't be able to do this for any bank other than Barclays.

	Goldman	JP Morgan	Citibank	Wells Fargo	Barclays Bank
1	-6.5%	-9.5%	-11.4%	-1.9%	-6.8%
2	-3.2%	-4.6%	-7.9%	-0.2%	-4.7%
3	**-1.3%**	**-2.6%**	**-7.8%**	**-0.2%**	**-4.0%**
4	-1.2%	-1.2%	-5.9%	0.0%	-4.0%
5	**-0.5%**	**-0.4%**	**-3.6%**	**0.0%**	**-2.9%**
6	-0.4%	-0.3%	-1.1%	0.2%	-2.9%
7	-0.2%	-0.3%	-0.8%	0.3%	-2.5%
8	-0.1%	-0.2%	-0.5%	0.3%	3.0%

Figure 30. Rates of change in shareholders' equity return series

So it would be useful to explore an alternate method that is not limited by how finely cut our change in shareholders' equity distribution is. **Enter Method Two.**

2. Method Two: Estimating Economic Capital

Method Two is a variation of Method One designed to provide additional flexibility in estimating probability of capital shortfall in the event of market or regulatory intervention. If you are comfortable with value-at-risk models, the first approach follows or uses the historical simulation model; the second follows the variance covariance model.

Of our original seven steps, four steps remain the same. The new step is calculation of shareholders' equity volatility. Our mechanism for calculating distance to threshold and our approach to calculating economic capital also changes.

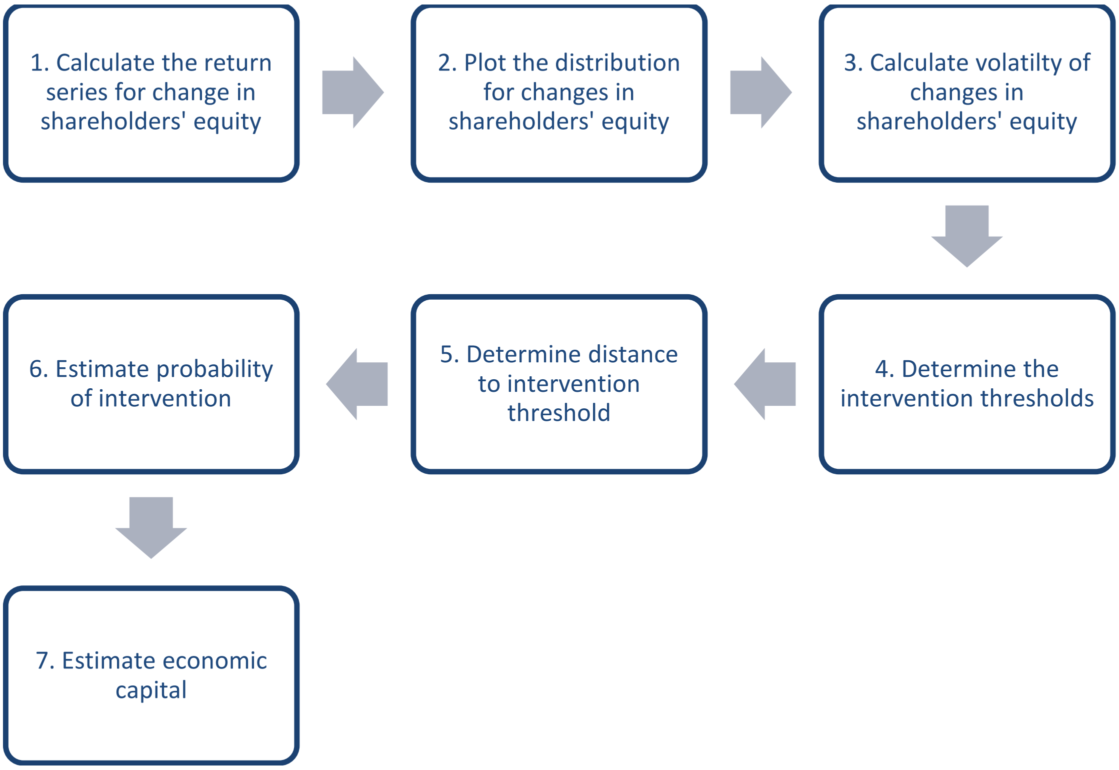


Figure 31. Model process: Method Two

Step 3. Volatility of shareholders' equity

Calculating volatility of shareholders' equity is a simple extension of our VaR return series approach. We calculate the quarterly change from one quarter to the next. The series represents the percentage change. We then use the Excel standard deviation function on the series to determine the quarterly volatility figure. (See Farid [2011] for a calculating return series for VaR tutorial). Multiply the result by square root of 4 to get an annualized volatility estimate and we end up with the series shared below.

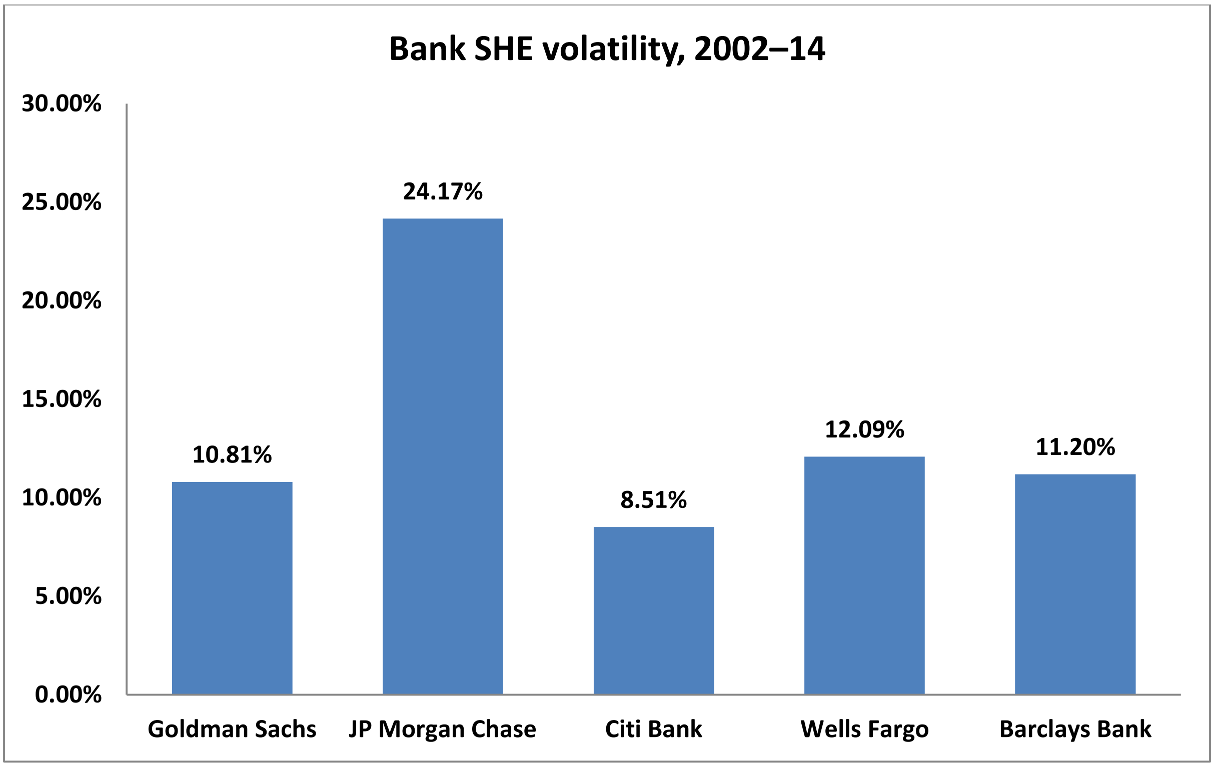


Figure 32. Annualized volatility estimates for rates of change in shareholders' equity, 2002–14

Step 4. Determine the intervention threshold

The intervention threshold remains the same as Method One. From a capital adequacy perspective, this threshold has been set at 10 percent. When a bank falls below the 10 percent threshold, model expectation is that either the regulator or market forces will react and intervene.

Step 5. Determine distance to intervention threshold

To estimate the distance to threshold, we need to translate our annualized volatility estimate to an absolute annual amount. This is the amount that will reduce shareholders' equity in the event of a worst-case loss.

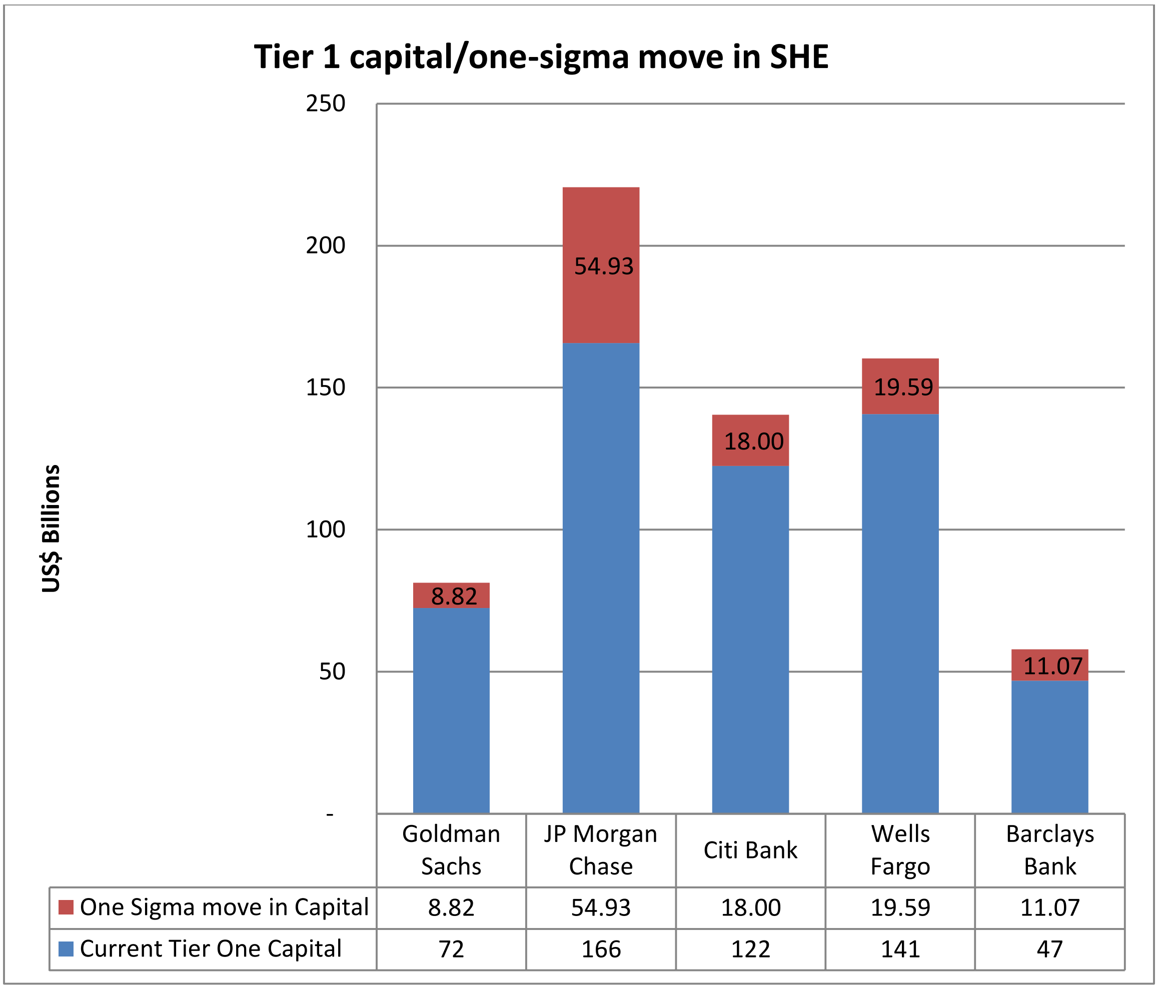


Figure 33. Distance to intervention for a one-sigma move

We express these losses in terms of volatility. A one-sigma loss is the current shareholders' equity balance multiplied by one unit of volatility. A two-sigma loss is two standard deviation, three-sigma is three. The chart above expresses these losses in terms of one-sigma shock—a shock that is within the range of a single standard deviation move in shareholders' equity.

Distance to intervention threshold is also measured using sigma moves. To calculate it, we refer back to our minimum regulatory capital threshold calculations to determine our estimate for excess regulatory capital stock.

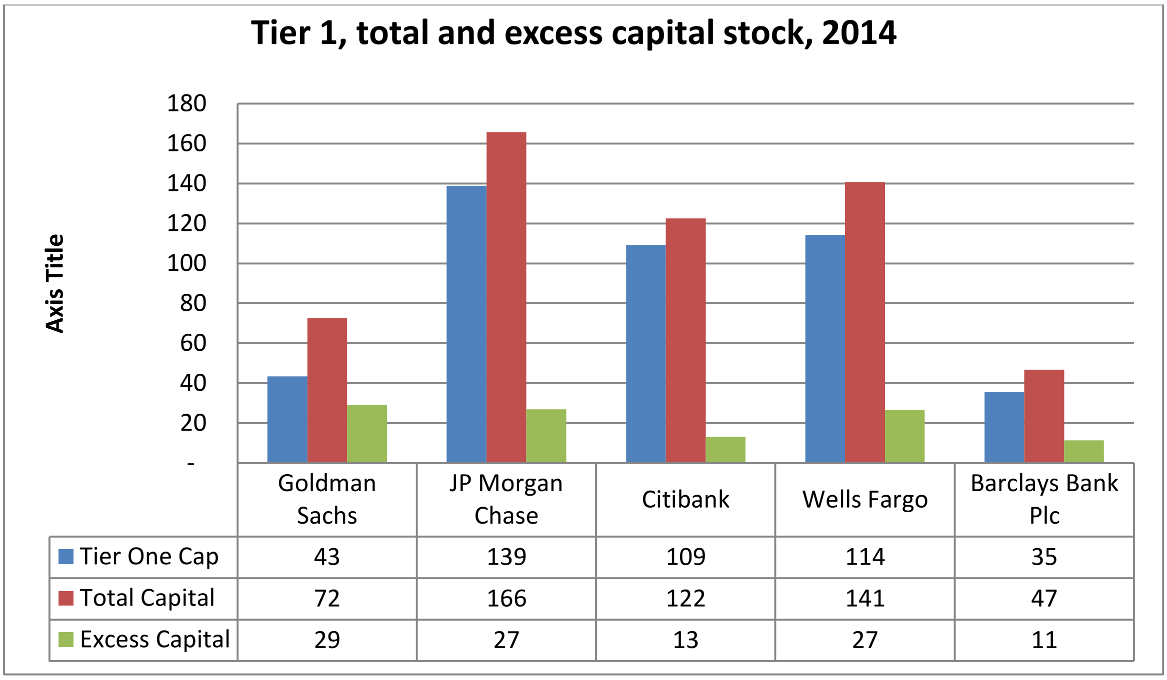


Figure 34. Tier 1, total and excess capital stock, 2014

Armed with the original excess regulatory capital figure, we estimate the number of sigma moves needed to wipe out the excess capital buffer. Remember, as per our model, intervention happens not when the capital is completely utilized but as soon as the bank in question falls below a regulatory or market intervention threshold.

While Citibank and Barclays have received more than their fair share of coverage, a number of market participants believe JPMorgan Chase and Wells Fargo are safe banks when compared to the likes of Goldman Sachs. We were just as surprised by the results of Method One but we internally justified that anomaly by the recent hits taken by JPMorgan Chase on account of the London Whale. Our second model is less impacted by extreme scenarios and more by average volatility. Will the same results still hold? Or will we see a different trend when it comes to these five banks?

The next graph presents our model results. Here is how you should read it. The higher the blue line, the more safe the bank in question is in terms of capital adequacy. So Goldman Sachs does very well by that standard. The other four are more or less in the same category but, surprisingly, Citibank is rated higher than JPMorgan Chase.

The higher the red line, the more capital the bank in question needs. Once again, Goldman Sachs does well by this standard and JPMorgan Chase is once again ranked the lowest of the lot.

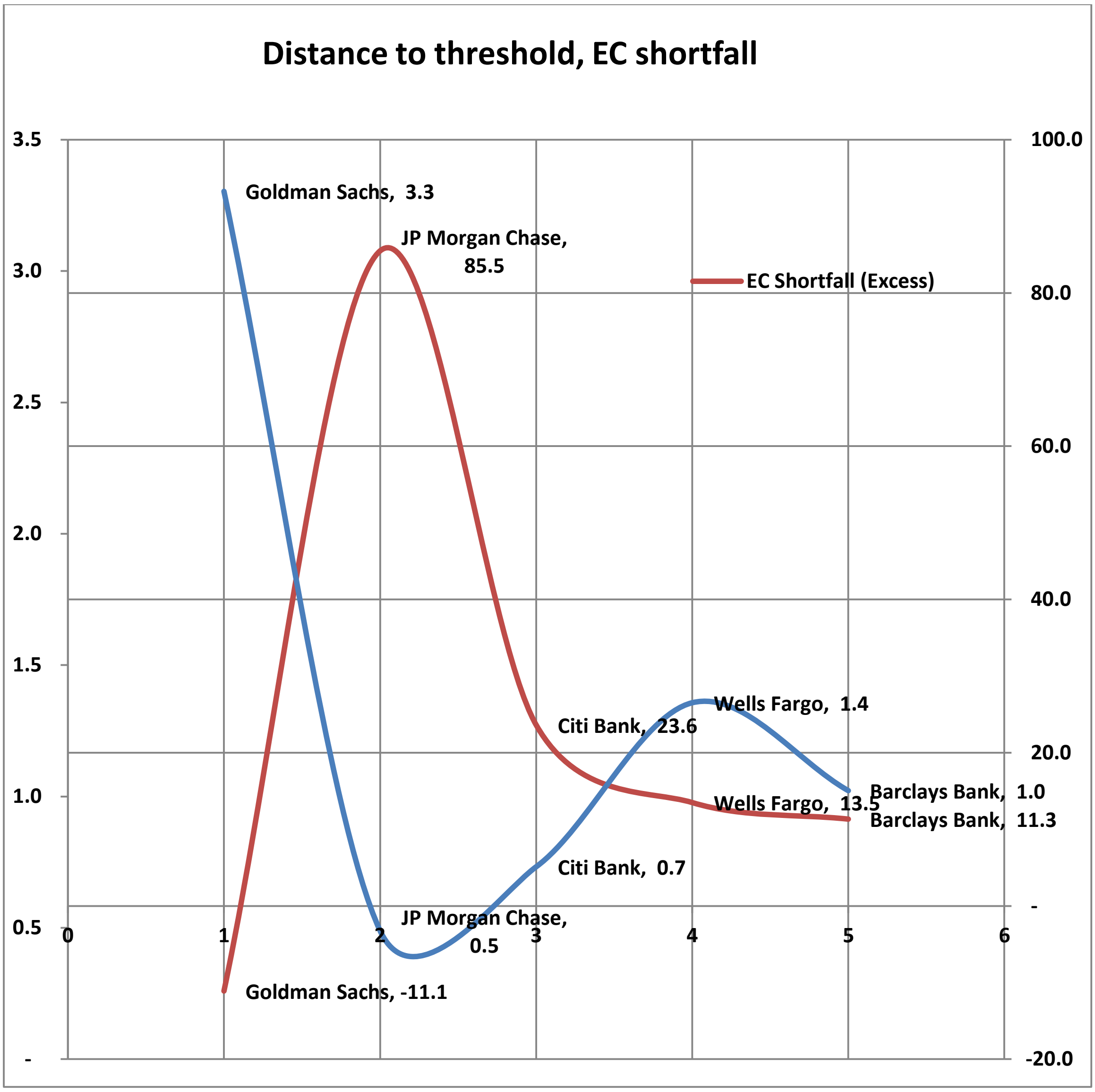


Figure 35. Distance to threshold and economic capital shortfall

How do you translate these results to probability of intervention? Remember here intervention does not mean default. It means that you are now likely to be on the receiving end of either a regulatory intervention or a market-based intervention. A regulatory action is generally smoother and, to be successful, must work at the speed of a lightning strike. However, there have been instances where the strike has gone south.

A market intervention is essentially a run to the exit by counterparties and tends to be disorderedly and chaotic. If the bank is large enough, it can create ripple effects that traverse the globe.

We apply a simple NORMSDIST function to the distance to threshold to assess the probability of such a move. The results are shared below.

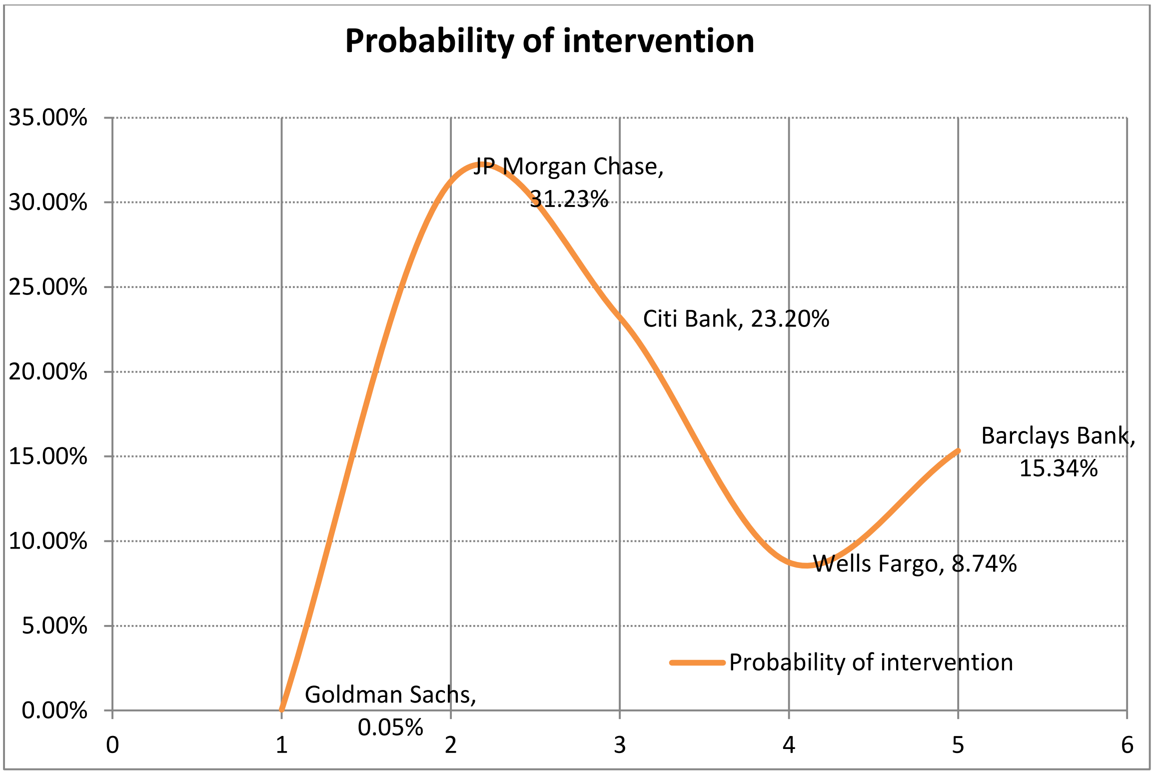


Figure 36. Probability of intervention

Once again, Goldman Sachs does better by this standard among the lot and JPMorgan is ranked the lowest.

While probabilities are nice, if we were to compare apples to apples and not oranges, it would be useful to compare the results for economic capital requirements across the two models, especially since Method One is a little restricted when it comes to calculating probabilities. Here are the results.

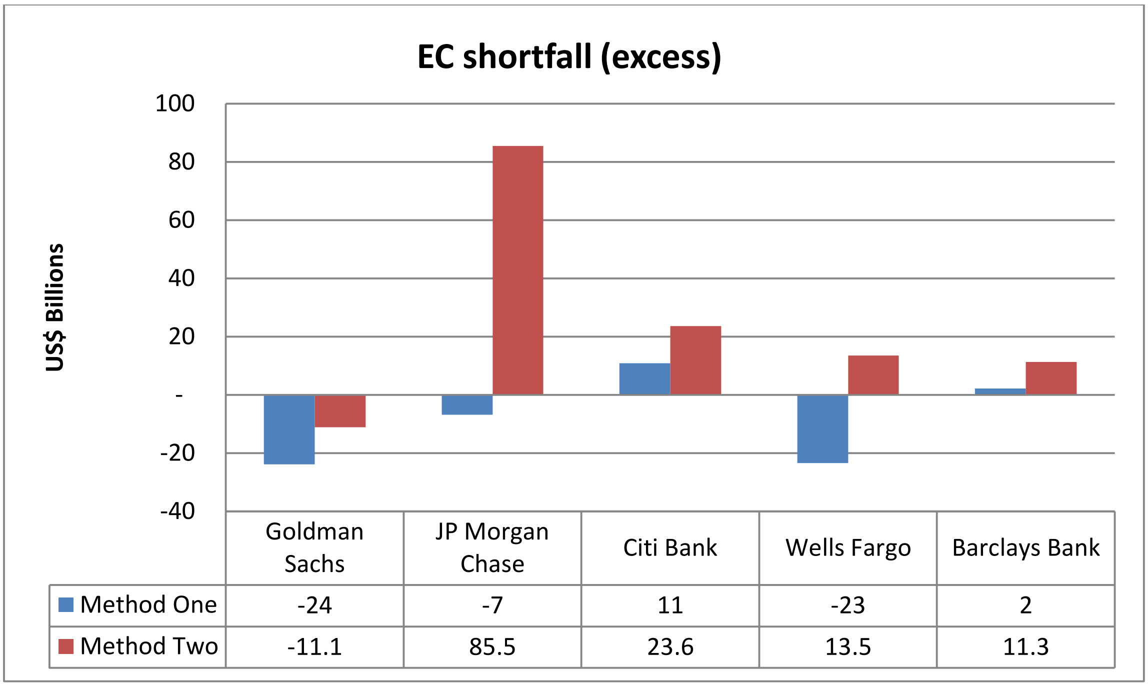


Figure 37. Excess of economic capital shortfall comparison

3. Reconciling the Difference in Results for the Two Approaches

There is a reason for the significant difference in economic capital estimates for the two approaches across our universe of five banks. **Method One** works with a worst-case loss estimate and assumes that the threshold for economic capital is equivalent to three worst-case losses that occur in a sequence. **Method Two** works with estimated volatility and assumes that a distance to intervention threshold of 3 (expressed in terms of shareholders' equity volatility) provides sufficient protection. Method One works with the true underlying distribution, Method Two assumes normality when it estimates distance to intervention threshold.

Given how our data set is structured, the probability of such an event occurring (three consecutive worst-case losses) is 0.00085 percent. Alternatively, it corresponds to a confidence level set at 99.99915 percent. We can try and calibrate Method Two using this approach by using 4.3 as a required distance to threshold rather than 3.0 in our model.

An alternate approach is to use Method One with a required distance to threshold of 1. This implies a single worst-case loss. This represents a probability of occurrence of 2.04 percent and a Z-score of 2.05, which we can use in Method Two. When we plug in the two numbers in our models, the results are still quite different from each other.

As per Method One, other than Citibank and Barclays, all banks in our data set are reasonably capitalized from an economic capital point of view. Citibank and Barclays need an additional injection of capital. As per Method Two, other than Goldman Sachs, all banks need a significant injection of economic capital.

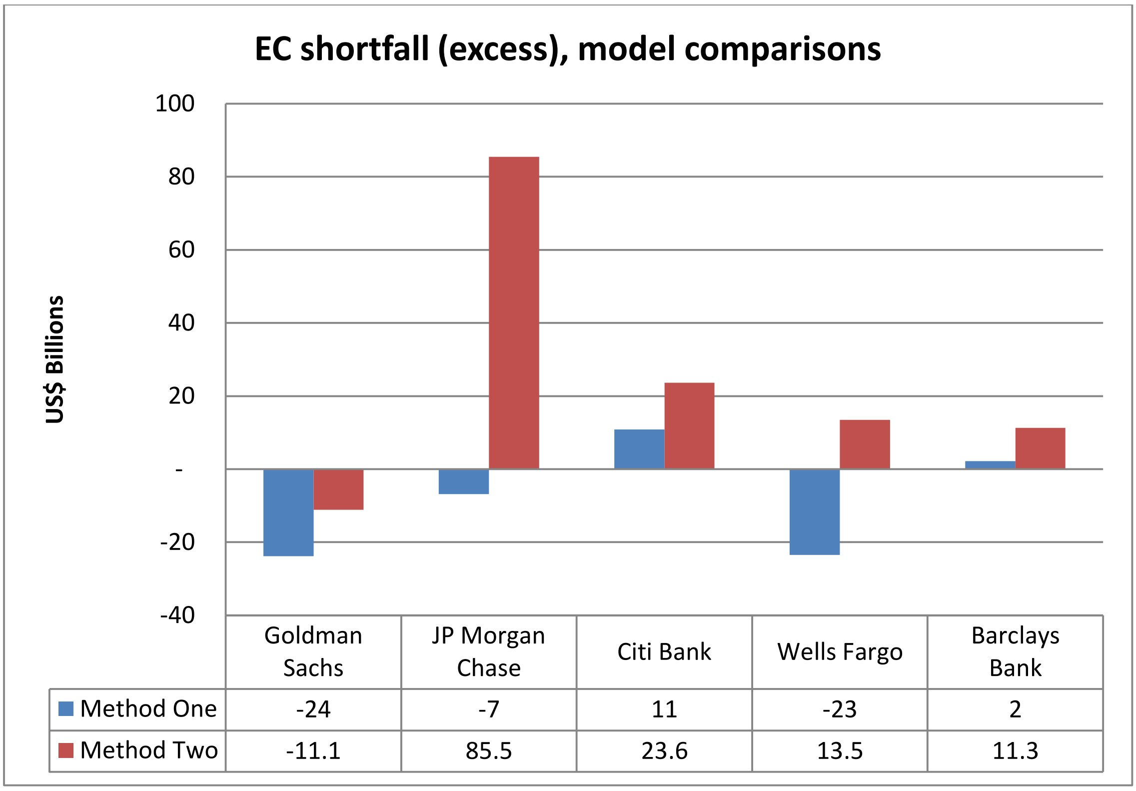


Figure 38. Excess of economic capital shortfall model comparison

a. Using an Intervention Trigger Other Than Capital Adequacy

The challenge with methods One and Two is that they use capital adequacy as the determining factor for estimating economic capital. Is capital adequacy a good measure of underlying financial risk? Are there better measures available? Within the risk and capital estimation, world participants generally have issues with the responsiveness of capital adequacy ratio to market-based changes. It is an interesting paradox given that both the original as well as the revised Basel regulatory frameworks for bank supervision are built around the capital adequacy measure.

For North American regulators, the preferred regulatory ratio is leverage (Eavis 2014). There is a reason for their discomfort with capital adequacy as the prime protector of the banking system (Farid 2013). Sheila Bair, chairperson of the Federal Deposit Insurance Agency (FDIC) during the financial crisis, makes her thoughts on this issue very clear in her book (Bair 2012) where she comes out clearly in favor of leverage ratios rather than capital adequacy as a measure of risk inherent in bank balance sheets.

Tier 1 leverage ratio uses Tier 1 capital rather than the entire capital stock. Under the capital adequacy guidelines provided by Federal Reserve Board (FRB) regulations (12 CFR Part 225, Appendix D), Tier 1 leverage ratio is calculated by dividing Tier 1 capital by the firm's average total consolidated assets.

Leveraging capital requires a significant amount of monitoring within financial services. There is a fine line between too little and too much. This fine line lies between the risk of default or insolvency and inefficient utilization of capital. The problem is that bank runs and name crisis, once triggered, can kill a perfectly healthy bank by the exit pressure wave they create. While on paper a bank's leverage ratio may be considered reasonable, once the market decides to turn and starts calling in to collect, leverage ratio can sink fast.

Banks that are of the highest standard under BOPEC (Bank subsidiaries, Other subsidiaries, Parent, Earnings, Capital) are required to main a Tier 1 leverage of 3 percent. New regulation recently raised this to 5 percent for banks with assets over $700 billion. Banks that have a significant impact on financial markets are encouraged to maintain a minimum leverage of 6 percent. Other banking institutions are required to maintain a Tier 1 leverage ratio of 4 percent.

Given the way the leverage ratio is calculated, the higher the regulatory leverage ratio, the better.

4. Method Three: Using Leverage Ratio

Method Three follows the same process we have used earlier. We create a trail of leverage ratios starting from 2002 and ending at 2014 for the five banks. Using the trail, we calculate the quarterly shift in ratios for each banks in our sample. The shifts (return series) will be used to estimate volatility. Volatility will be used to estimate the probability that the ratio for a given bank in question will fall below the intervention threshold.

For the purpose of this note and the economic capital case study, we will use FRB regulations. Because of the limitation of our public data, we will use the shareholders' equity as a proxy for Tier 1 capital for calculating Tier 1 leverage ratio.

The revised and simplified Tier 1 leverage ratio formula is:

$$\text{Tier 1 leverage ratio} = \frac{\text{Shareholders}' \text{ equity}}{\text{Total assets}}$$

Here is what the revised process looks like:

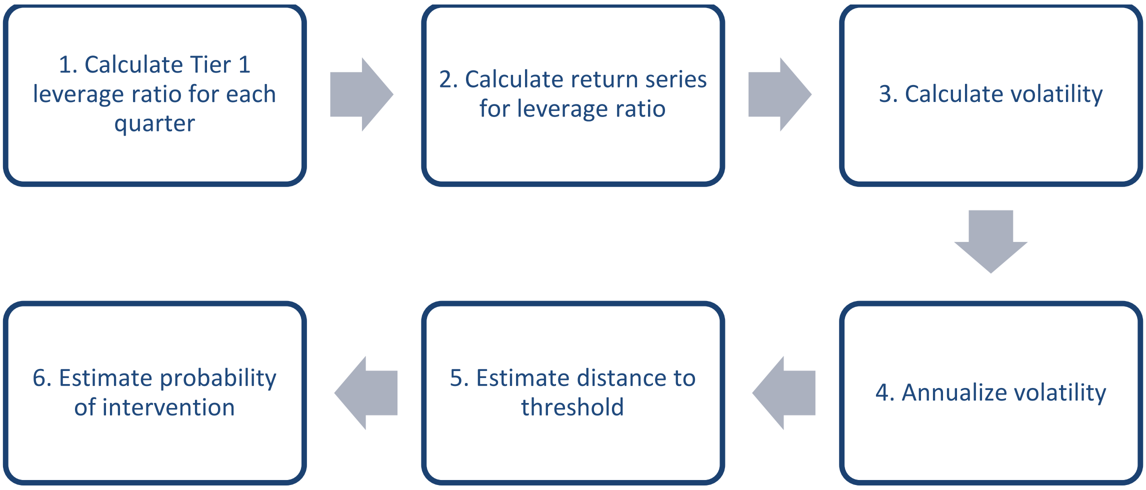


Figure 39. Model process: Method Three

There are two ways of reviewing the trail of leverage ratios. The first is to calculate trailing leverage, a plot of leverage ratios from one quarter to the next. The second is to use the trail to plot the histogram produced when we review the change in leverage ratio from one quarter to the next.

We look at both series. As per the regulatory guidelines discussed earlier in this note, large, influential U.S. banks need to maintain their leverage ratio within a certain range. We see that regulation at work for four of the five banks in our sample. Barclays falls under U.K. guidelines that require a 4 percent threshold, less than half of that required of U.S.-domiciled banks.

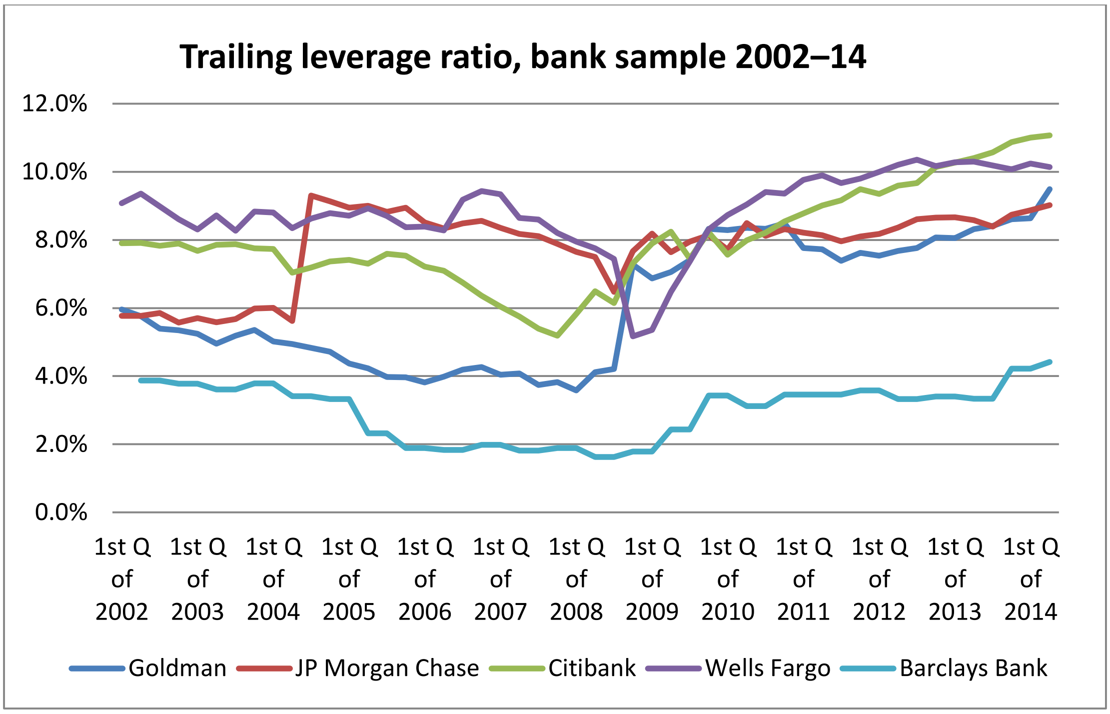


Figure 40. Trailing leverage ratio, banks sample, 2002–14

While the plot above give us an indication of where U.S. banks have been when it comes to leverage ratio, it doesn't really help in answering the "where they will be in the near future" question.

For that, we need our distribution of quarter-to-quarter changes in the leverage ratio as well as the recorded volatility in that ratio over the last 12 years. Both set of graphs follow for the five banks in our sample.

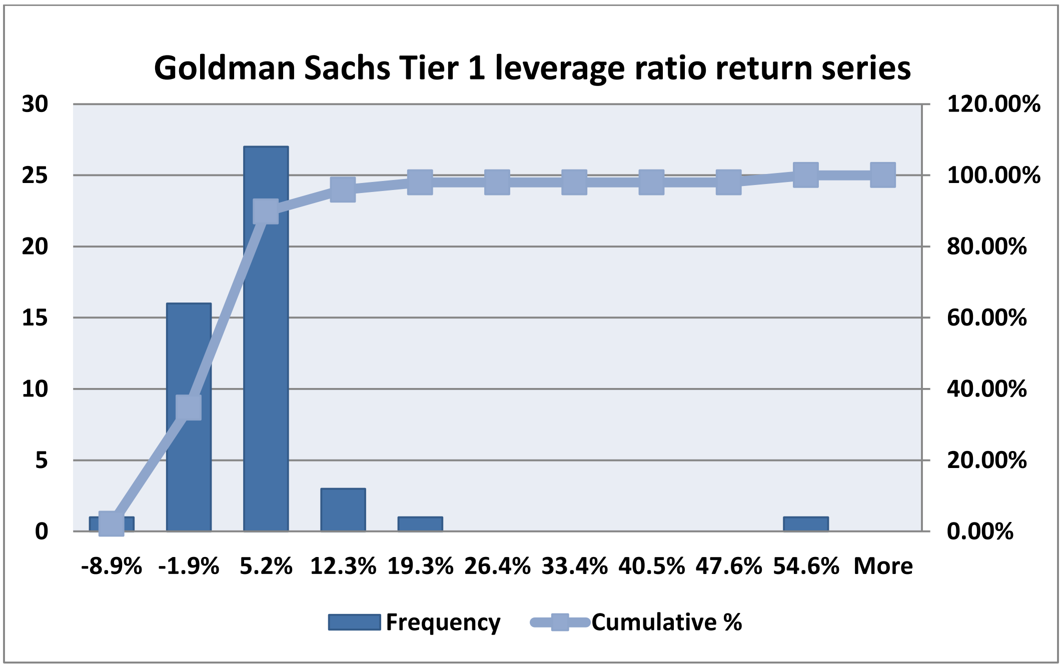


Figure 41. Tier 1 leverage ratio returns distribution, Goldman Sachs

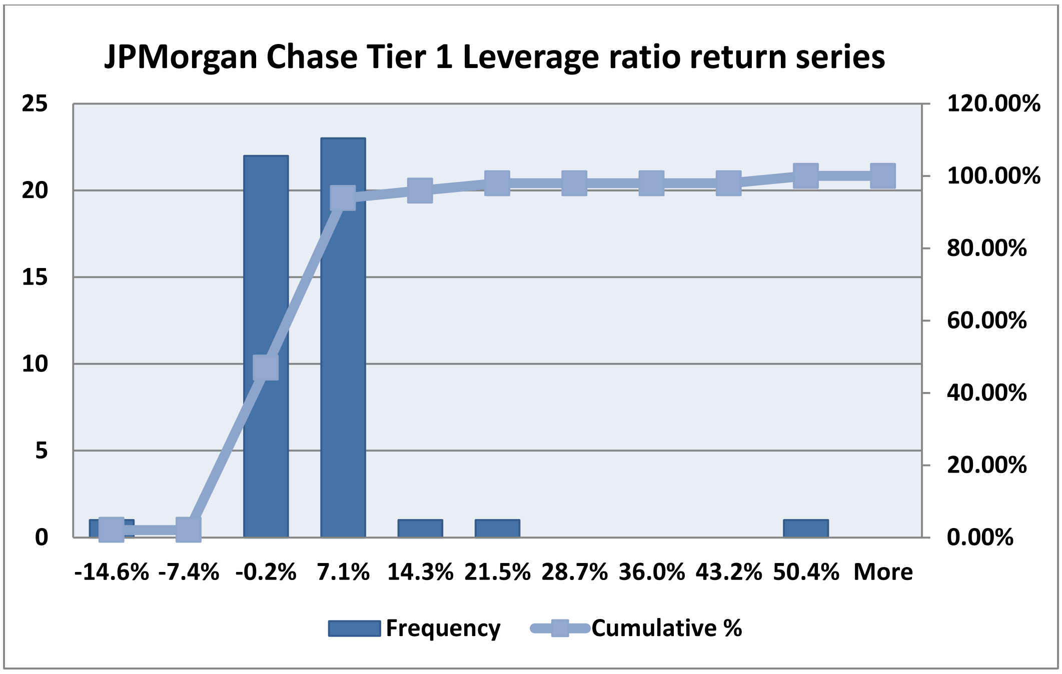


Figure 42. Tier 1 leverage ratio returns distribution, JPMorgan Chase

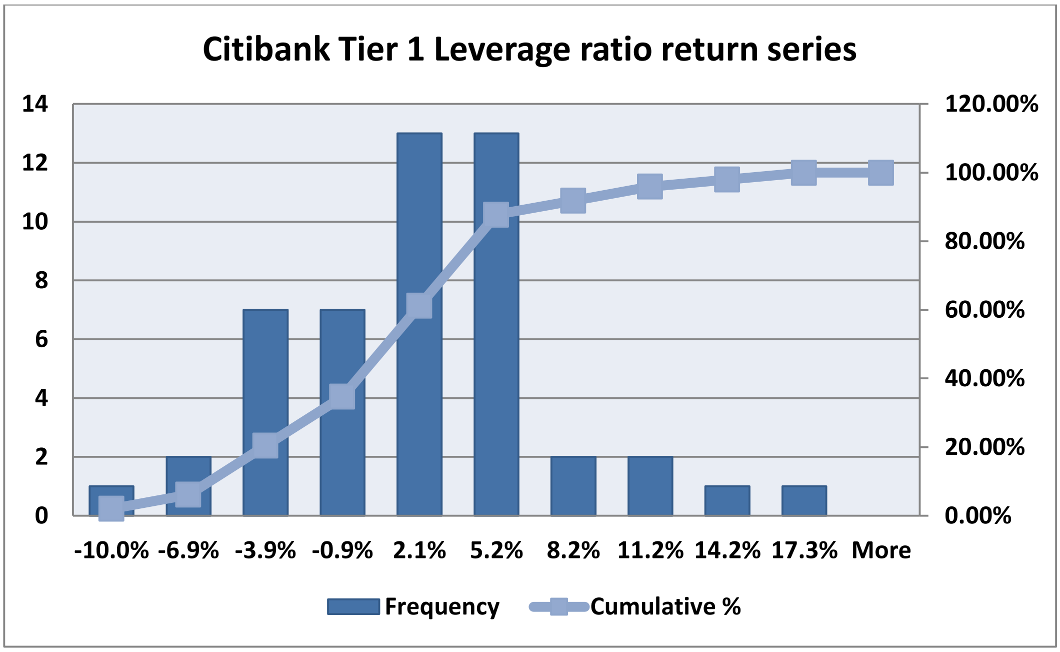


Figure 43. Tier 1 leverage ratio returns distribution, Citibank

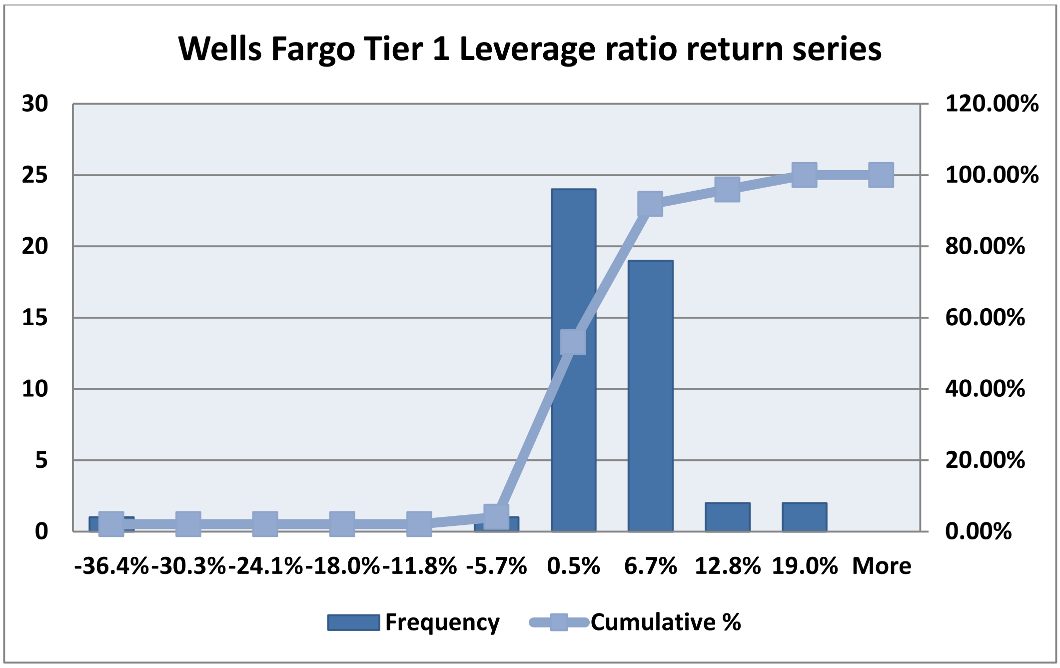


Figure 44. Tier 1 leverage ratio returns distribution, Wells Fargo

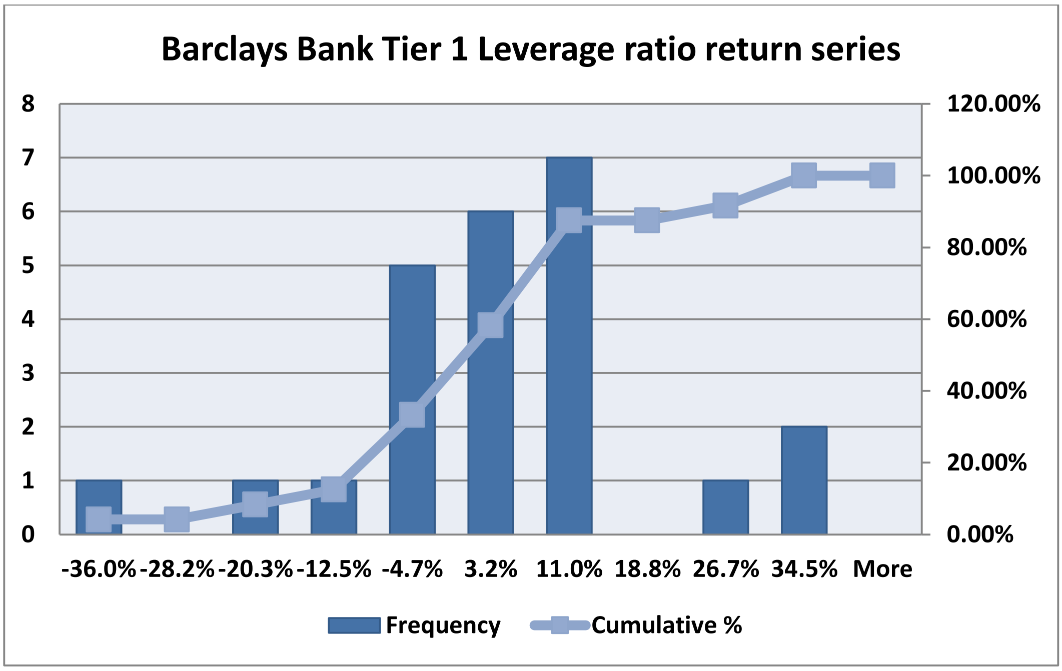


Figure 45. Tier 1 leverage ratio returns distribution, Barclays Bank

Using the original trail and distribution of changes (return series), calculating volatility follows the same process we have used in our earlier method. The annualized volatility figure for the five banks is presented below. Other than Barclays, the estimate is based on quarterly changes. For Barclays, the estimate is based on semiannual returns.

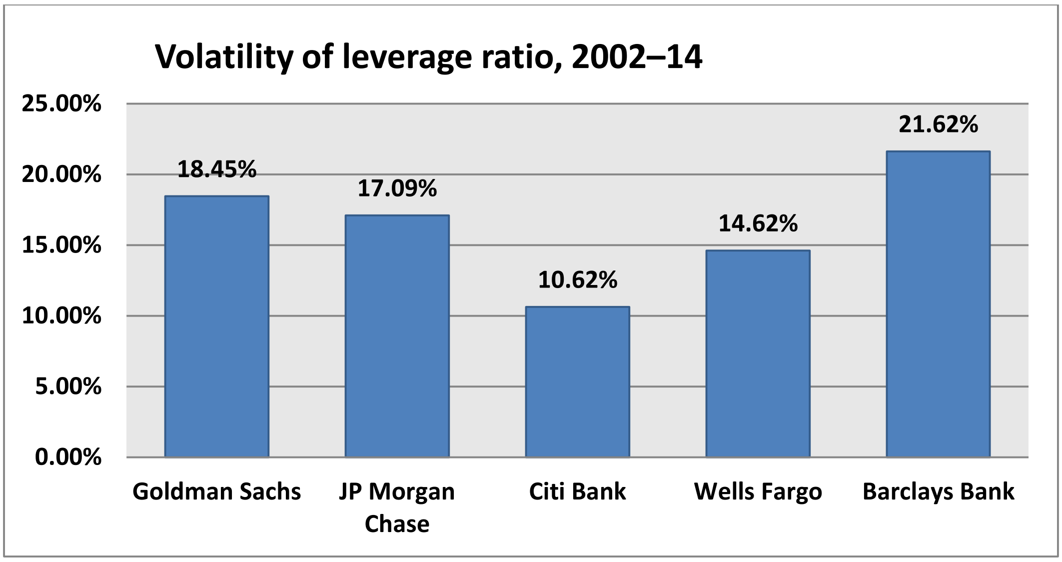
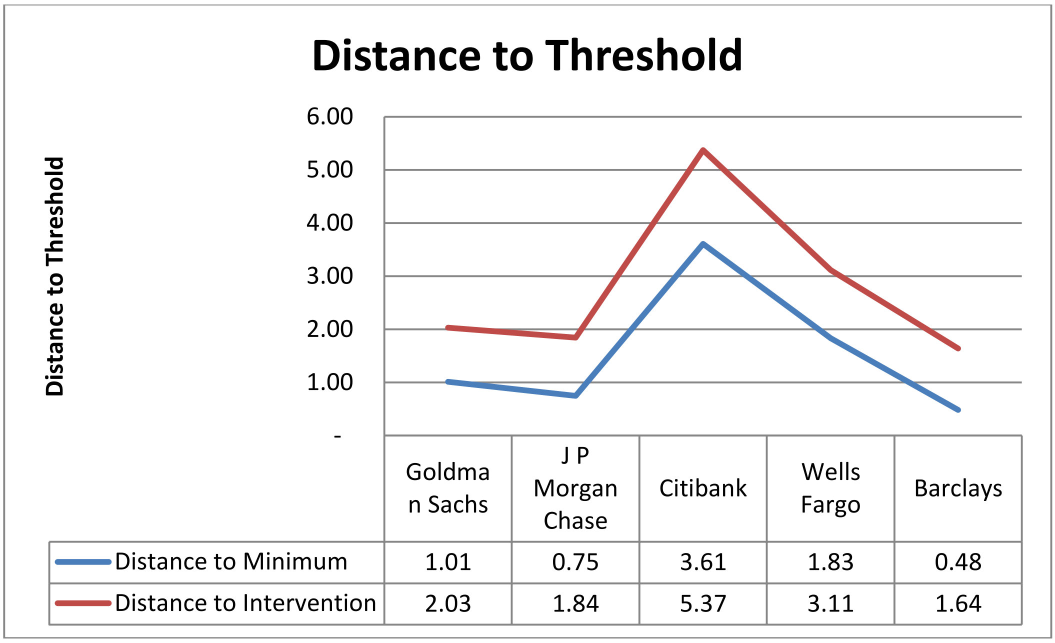


Figure 46. Volatility of leverage ratio returns, 2002–14

Now that we have volatility, we need to estimate distance to threshold. For leverage ratio, we set two thresholds. The first is the minimum required regulatory leverage ratio. For the banks in our sample, this is 8 percent for the first four and 4 percent for Barclays.

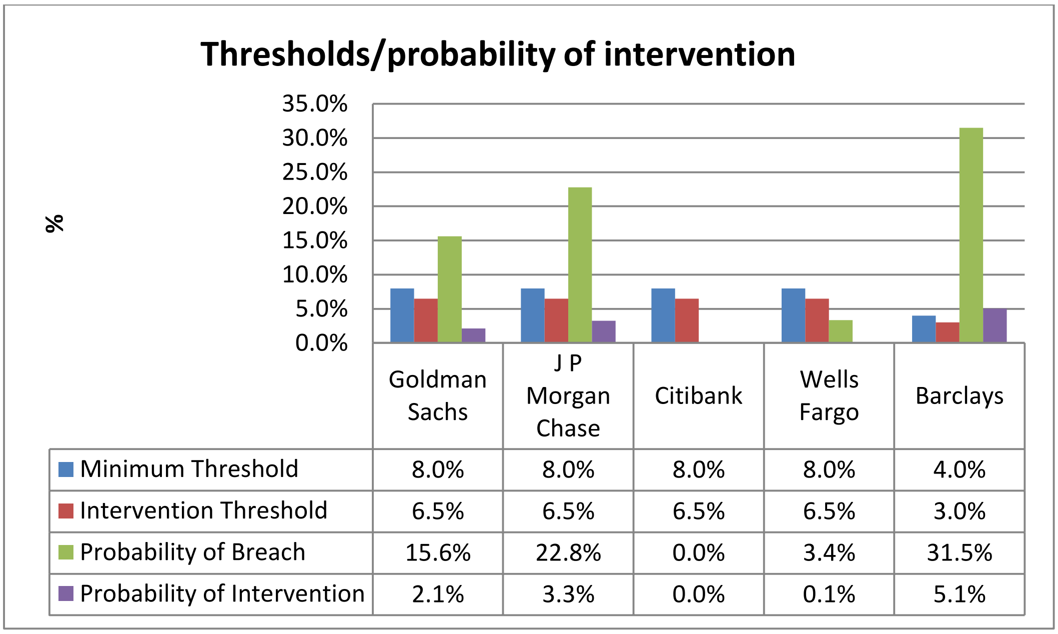
A bank may breach the minimum leverage ratio requirement for short intervals and most regulators would give some breathing room if the breach is addressed and does not recur frequently. However, there is a second threshold beyond which the regulator will have no option but to intervene because if they didn't, markets would intervene. Since we have two thresholds, we use them to determine distance to intervention. For the first four banks, the intervention threshold is set at 6.5 percent. For Barclays, we set it at 3 percent. Distance to both thresholds and probability of intervention are presented next. The lower the distance, the higher the probability of intervention.



	Goldman Sachs	J P Morgan Chase	Citibank	Wells Fargo	Barclays
Distance to Minimum	1.01	0.75	3.61	1.83	0.48
Distance to Intervention	2.03	1.84	5.37	3.11	1.64

Figure 47. Distance to threshold

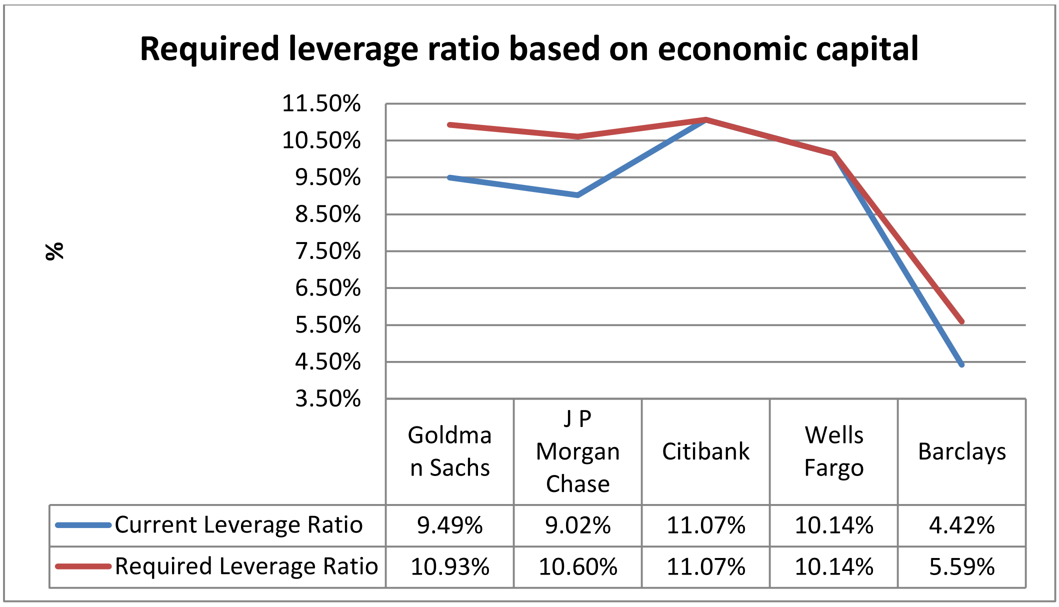
The big surprise using leverage ratio as a tool for estimating probability of intervention is Citibank.



	Goldman Sachs	J P Morgan Chase	Citibank	Wells Fargo	Barclays
Minimum Threshold	8.0%	8.0%	8.0%	8.0%	4.0%
Intervention Threshold	6.5%	6.5%	6.5%	6.5%	3.0%
Probability of Breach	15.6%	22.8%	0.0%	3.4%	31.5%
Probability of Intervention	2.1%	3.3%	0.0%	0.1%	5.1%

Figure 48. Probabilities of breach and intervention

To estimate economic capital, we now need to define an acceptable probability of intervention at the board level. If that probability threshold is set at 0.1 percent, Citibank and Wells Fargo are adequately capitalized. But Goldman Sachs, JPMorgan Chase and Barclays need additional capital.



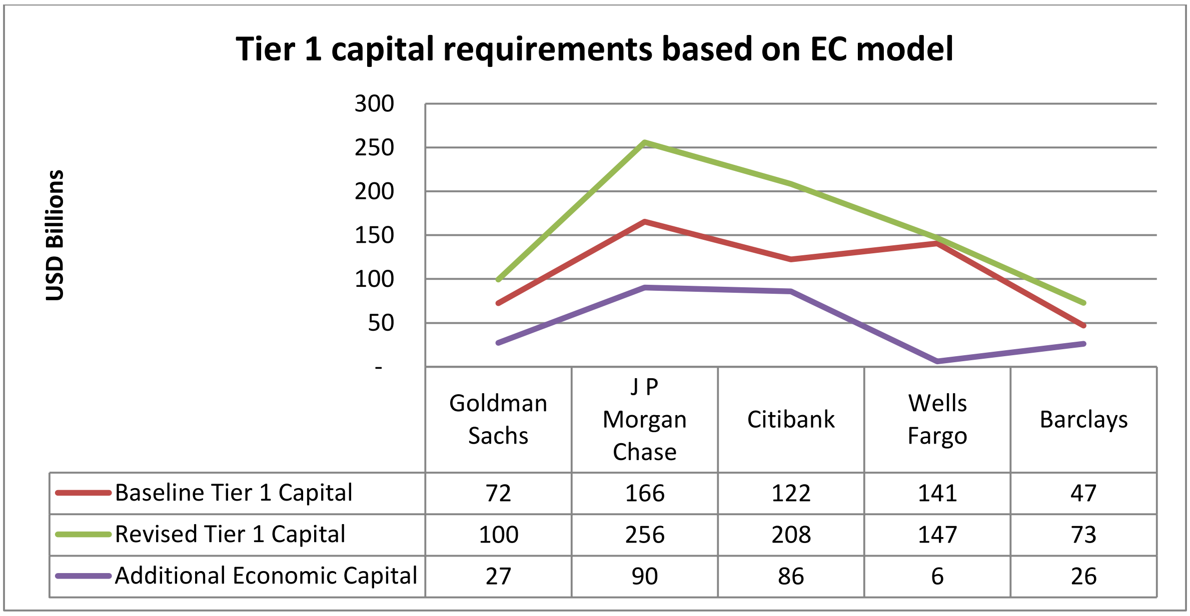
	Goldman Sachs	J P Morgan Chase	Citibank	Wells Fargo	Barclays
Current Leverage Ratio	9.49%	9.02%	11.07%	10.14%	4.42%
Required Leverage Ratio	10.93%	10.60%	11.07%	10.14%	5.59%

Figure 49. Required leverage ratio based on economic capital

But, wait, there is an issue.

If you remember correctly, we took a simplifying assumption when we described our data set. From a regulatory point of view, we are interested in the Tier 1 leverage ratio. Because of our data set issues, we used shareholders' equity as a proxy for core capital.

That problem can now be easily fixed. Now that we have our results and we have estimates for the most recent quarter of capital levels, we can determine how much additional core capital is required.



	Goldman Sachs	J P Morgan Chase	Citibank	Wells Fargo	Barclays
Baseline Tier 1 Capital	72	166	122	141	47
Revised Tier 1 Capital	100	256	208	147	73
Additional Economic Capital	27	90	86	6	26

Figure 50. Tier 1 capital requirements based on Method Three

Conclusions

Starting with an initial look at economic capital, we reviewed three approaches for using accounting data for estimating economic capital. Our banking case study also showcases how publicly available financial information can be used to reach interesting conclusions about Main Street banks. A copula-free approach brings many advantages with it, the most significant of which is reduction in modeling assumptions and model simplification.

With the benefit of technological systems, most banks today generate a daily balance sheet and P&L statement. While not as accurate and as current as month-end (monthlies) statements, a bank generating daily statements can easily deploy the approach described in this paper and compare it with the results generated by its existing capital model.

While accounting data is not always the perfect proxy for reality, its quality has improved over the last two decades. We have also seen numerous instances where sophisticated correlation models have failed under times of stress. The copula-free approach provides an alternate methodology using an implicit correlation assumption that may be easier to explain and present to both board members and bank regulators.

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