

## *Value-at-Risk: A Dissenting Opinion*

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The classical theorists resemble Euclidean geometers in a non-Euclidian world who, discovering that in experience straight lines apparently parallel often meet, rebuke the lines for not keeping straight – as the only remedy for the unfortunate collisions which are occurring. Yet, in truth, there is no remedy except to throw over the axiom of parallels and to work out a non-Euclidian geometry.

John Maynard Keynes, *The General Theory* (1936)

### **HOW TO BLOW UP YOUR HEDGE FUND**

The partners of Long-Term Capital Management included Nobel Prize winners and PhDs in finance, economics, maths and physics. Having poached Wall Street's savviest traders and combined them with what no less a figure than William Sharpe declared to be "probably the best academic finance department in the world" (Siconolfi and Raghavan 1998), LTCM set about deploying the most sophisticated financial models ever devised. Key among these models was value-at-risk (VaR).

The VaR methodology was integral to LTCM's investment strategy. LTCM viewed portfolio construction as an optimisation problem centred on maximising returns while minimising variance (which in VaR terms is the same thing as minimising "risk"). The end goal of LTCM's process was to produce superior "risk-adjusted" returns over the long term – high returns with low variance.

From LTCM's inception in 1994 through 1997, the strategy

worked, generating a compound annual return over the four-year period of nearly 30% / year, with a variance lower than that of the broad US stock market. The fund appeared to be a wildly successful marriage of theory and practice. The period of 1994 to 1997 only served to confirm the partners' faith in their models.

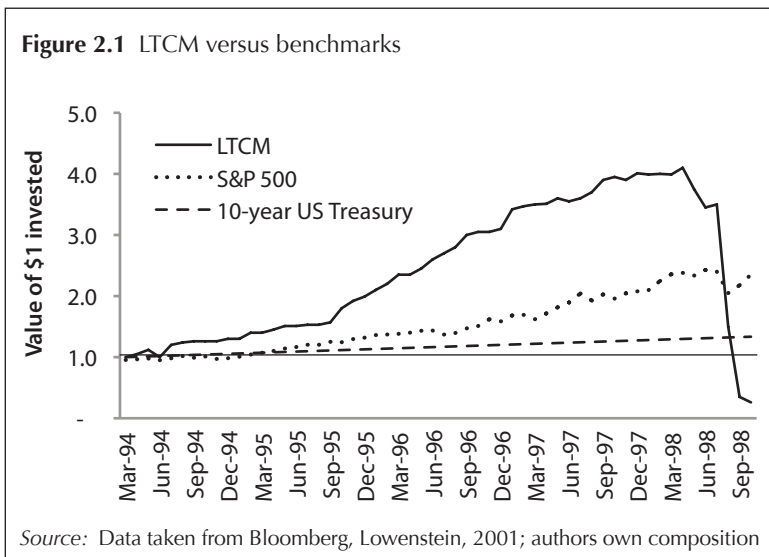
Despite the complexity and diversity of LTCM's portfolio, the partners believed they had distilled their risk profile down to a few simple numbers that could be succinctly captured in a VaR analysis. In a fit of hubris, LTCM disclosed these VaR analyses to their investors, indicating a daily standard deviation of US\$45 million and a monthly standard deviation of US\$206 million, against total capital of US\$5 billion (Jorion 2000). These figures were followed by the declaration of a 99% confidence level that the fund's losses would not exceed US\$105 million on a daily basis, or US\$480 million on a monthly basis.

However, in the summer of 1998, LTCM's "confidence levels" began to break down, at first slowly and then rapidly. In May, the fund lost US\$310 million. In June it lost US\$450 million, already nearing LTCM's partners' 99% confidence level of what losses could not exceed. Still, through June these losses could be understood within the well-defined limits of the model. After four very strong years, it stood to reason that LTCM would experience losses sometime, but that the fund would quickly return to profitability.

Such expectations proved unfounded. Losses for the month of August exceeded US\$1,700 million, an 8.3-sigma event according to LTCM's models. Assuming a normal (Gaussian) distribution, as LTCM did, an 8.3-sigma event should occur approximately once every 80 trillion years. It began to dawn on the partners that something might have gone wrong in their risk modelling.

The losses didn't come in the form of a gradual bleed. On August 21, 1998, the portfolio lost US\$550 million – in a single day. According to LTCM's VaR model, August 21 represented a 12.2-sigma event. The difference between an 8-sigma event and a 12-sigma event is such that the 8-sigma event, which should occur only once every tens of trillion years, should itself occur billions of times before even a single 12-sigma event occurs. Assuming a normal distribution, a 12.2-sigma event should be rare enough that it essentially breaks the model.

It can be tempting to just ignore this sort of event, except that just one month later LTCM lost another US\$550 million in a single day, on September 21. The reality began to sink in that the precise maths that went into and came out of the VaR model – the historical sampling, the covariance calculations, the 99% confidence levels – had proved deeply misleading about the real nature of the risks LTCM was taking. By the end of September, LTCM had lost 92% of its partners' capital, more than US\$4 billion dollars, and almost certainly would have lost it all had the Federal Reserve not intervened to force an orderly liquidation (Figure 2.1).



Subsequent events have proved that 1998 was not a one-off “perfect storm” that we can expect never to see again. The market action that bankrupted LTCM in 1998 – ballooning credit spreads and spiking equity volatility – was only a fraction of the magnitude of what happened in 2007–2008. As Eric Rosenfeld, one of the LTCM partners, conceded in a 2009 presentation at the Sloan School of Management, if LTCM had somehow survived 1998, its collapse in 2007–2008 would have been orders of magnitude more spectacular.

Not only did LTCM’s VaR models fail to prepare them for a market event that in retrospect appears to occur about once per decade,

but LTCM's VaR models encouraged a portfolio construction that rendered the firm uniquely vulnerable to that event. The case of LTCM is instructive because it reveals the three fundamental weaknesses inherent to the VaR methodology: (1) the false assumption of a normal distribution and therefore a unique vulnerability to the problems presented by fat tails; (2) a naïve equation of variance with "risk"; and (3) the problems inherent in using the past to predict the future.

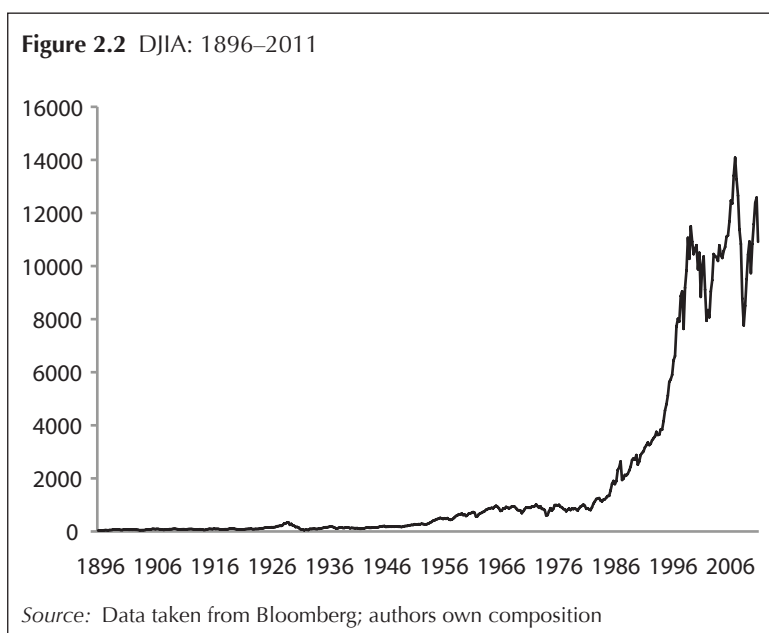
The remainder of this chapter will discuss each of these three points.

## NOT ALL DISTRIBUTIONS ARE NORMAL

### Some data; non-linearity of returns

The first question that needs to be addressed is why, in practice, firms relying on VaR fail so frequently.

Some historical data helps to clarify the picture. To take the most familiar example, since its inception in 1896, the Dow Jones Industrial Average (Figure 2.2) has had more than 29,000 trading days. Over this period, the index has demonstrated a daily standard deviation of 1.16%.



Assuming a normal (Gaussian) distribution of returns, as the VaR model does, we should expect to find 98% of the daily moves of the index to fall within a range of 2.33-sigma (in this case a daily change of about  $\pm 2.69\%$  around the mean daily return of 2.6bp). In other words, the theory predicts that the index should have exhibited either a positive or negative move around the mean of a magnitude greater than 2.69% about 574 times – in theory. In the historical sample, the actual number was 918 (Table 2.1).

Again, assuming a normal distribution, over the 116-year history of the index we should expect to find about 80 observations beyond the 3-sigma level. In the 116-year sample, we observe 480 such instances.

Assuming a normal distribution, over the same 116-year period we should expect to find about two observations beyond the 4-sigma level. In the sample, we observe 202.

Assuming a normal distribution, we should expect to find a 5-sigma event approximately once every 7,000 years, a fair amount longer than the 116-year history of the index. In the historical sample, we observe 87 such instances over the 116 years, a little under one per year.

Assuming a normal distribution, we should expect to find a 6-sigma event once every 2 million years. In the sample, we observe 48, a little under one every other year.

Assuming a normal distribution, we should expect to find a 7-sigma event once every 1.5 billion years. In the sample, we observe 27, about once every four years.

Eight-sigma events should not occur even once over countless iterations of the history of the universe, yet in the sample we observe 20, about once every six years.

By the time we reach beyond 10-sigma events, the normal distribution predicts such events to be so infinitesimally rare that the probabilities are no longer meaningful to us. And yet in practice we've experienced 10-sigma events nine times in the last 116 years, or a little less than once per decade.

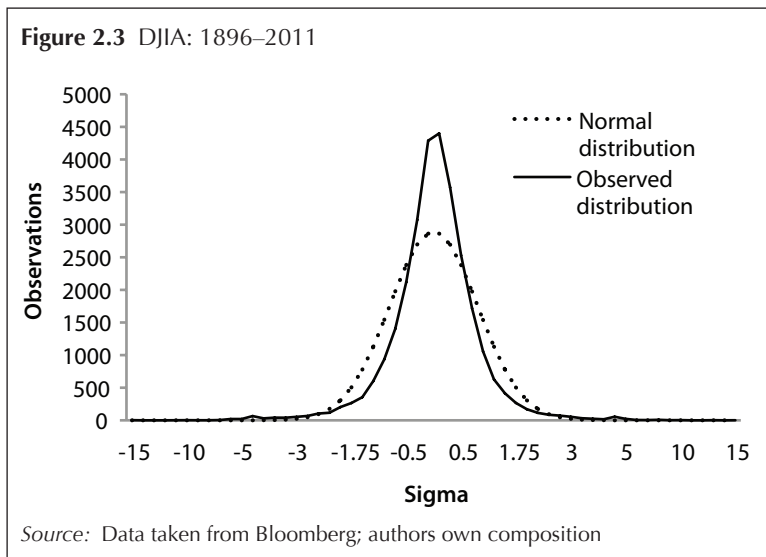
At the very far ends of the tails, we have December 14, 1914, an 18-sigma event, and of course October 19, 1987, a 20-sigma event. For practical purposes such events fall outside the bounds of the model.

**Table 2.1** 1-Day Events in the DJIA: 1896–2011

<b>Sigma</b>	<b>Expected</b>	<b>Observed</b>	<b>Error factor</b>
2.33-sigma	575	918	1.6
3-sigma	78	480	6.2
4-sigma	1.83	202	110.4
5-sigma	0.0166	87	5,240.9
6-sigma	0.0000573	48	837,696.3
7-sigma	7.43243E-08	27	363,272,718.9
8-sigma	0	20	infinite
10-sigma	0	9	infinite

Source: Data taken from Bloomberg; authors own composition

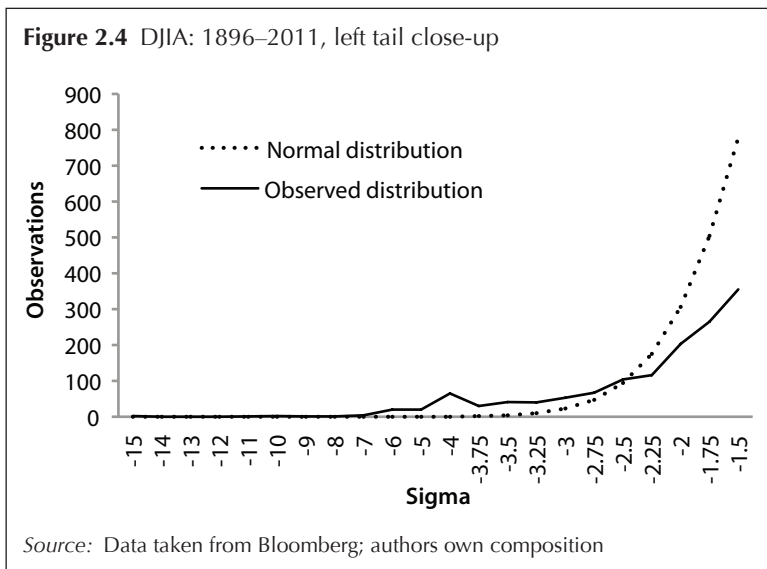
Thus, what the theory predicts and what actually happened represent wildly divergent sets of outcomes (Table 2.1). A normal distribution has not been a safe assumption over the last 116 years of the Dow (Figures 2.3 and 2.4).



This by itself isn't necessarily damning. We need not observe a perfect normal distribution in the real world in order to make use of mathematical tools that assume a normal distribution. After all, the important differences we see between theory and reality occur only at the extremes of the distribution. These extremes – the tails – by definition represent rare events. As outlined above, as the events become more extreme, the error factors increase by orders of magnitude into the trillions and beyond.

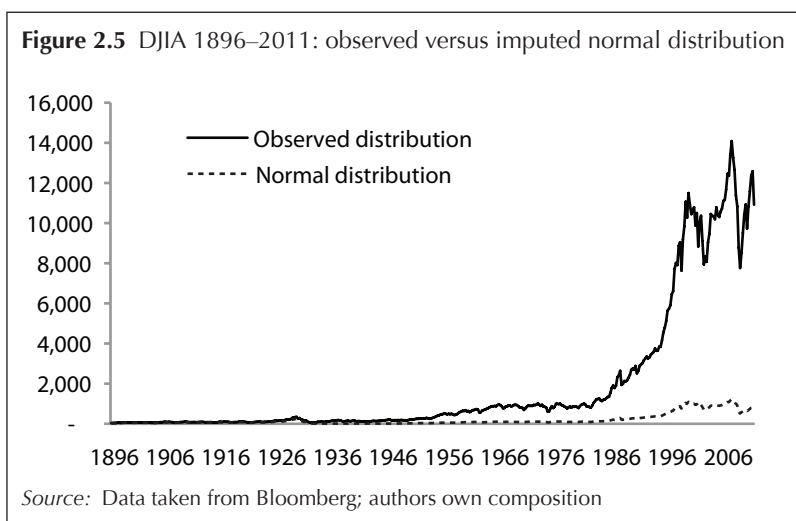
But, since these events are rare, the large error factors are equally rare. If instead we shift our focus towards the middle of the distribution, where the bulk of the observations lie, we see that about 80% of the Dow's trading days fall within 1-sigma, against the theory's prediction of 67%. Now we are talking about an error factor closer to 20%. Based on this, it might appear that VaR can still be useful for understanding the risks involved in more "normal" markets, even if it is less useful for predicting the frequency of extreme events.

This appearance is misleading. When we are talking about financial market risks, we cannot simply ignore the extreme events in favour of focusing on "normal" markets, because it is the extreme events that drive returns. The power of the tails is enormous, and their impact is not linear. This nonlinearity renders the results of tail analyses deeply counterintuitive.



Consider for a moment “upside” risk. If we were to remove the top 100 trading days – fat tails every one of them – from the 29,000-day sample, we would also be removing 99.79% of the cumulative return of the index over the last 116 years. In other words, 0.34% of the trading days – those concentrated in the tail – are responsible for more than 99% of the index’s cumulative return (Table 2.2).

To make a completely fair comparison, however, we need to replace the top 100 observed trading days with the top 100 trading days we would expect from a normal distribution of a 29,000-day sample. When we make this swap, the cumulative return over the 116 years drops by 93.5% compared with the actual historical return. The gulf between the normal distribution and the observed reality is so large that the difference between the two over just 100 days changes the cumulative impact of a 29,000-day sample by a factor of 15! (Figure 2.5)



Again, this impact is not linear. If we were to simply remove the top 10 trading days rather than the top 100, we would be removing 67% of the cumulative return over the 116 years. In other words, 0.034% of the trading days represent two-thirds of the cumulative 116 year return (Table 2.2). If we replace these 10 days with the returns predicted by the normal distribution, the cumulative return for the index drops by half.



It is extremely easy to underestimate the power of the tails.

**Table 2.2** DJIA: 1896–2011

Cumulative impact in the distribution	
Top 10 days	66.87%
Days 11–100	32.92%
Remaining 29,000 days	0.21%

Thus, even if we can safely assume that VaR works well during the 99% of the time that represents “normal” markets, this 99% of the time when VaR works accounts for less than 1% of the cumulative impact of the distribution. Because VaR is unable to account for what happens in the tails, it is unable to account for what actually drives risk and returns in financial markets. It is not a useful measure.

In terms of “downside” risk, the maths is equally compelling, but far more simple. A risk manager assuming a normal distribution into a VaR model could reasonably design a portfolio to withstand a 5-sigma event based on the expectation that the portfolio would make it through the next 7,000 years without a problem. Based on the actual record, we can expect such a portfolio to blow up approximately every 2.5 years.

This is a deeply flawed model.

### **Fat tails and the blackjack table**

Where the normal distribution is useful is for understanding games involving coin flips, or certain casino games, where, at a minimum, (1) the rules of the game are stable, linear and well-defined and (2) each individual iteration of the game can be treated as discrete. Such conditions are a prerequisite for creating the random walk that will, over time, generate a normal distribution. Thus, we can make predictions about a casino’s ability to make money on the craps table or the likelihood of flipping heads 100 times in a row with an extremely high degree of confidence.

Unfortunately, neither of these conditions obtains in financial markets. It is unsurprising, then, that over any meaningful period the actual, real-world performance of the financial markets has

failed to conform to a normal distribution. This is because (1) in the financial markets the rules aren't defined. In gambling terms, we don't know in advance how many sides the dice have, and we don't know if or how the number of sides on the dice is changing over time (Taleb 2001, 2007). And (2) the individual iterations are not discrete. In a casino game, rolling snake-eyes once does not increase the likelihood of rolling snake-eyes on the next roll. In the financial markets, it does (Mandelbrot and Hudson 2006)

Because of the power of the normal distribution, it can be tempting to treat markets as though they behave like a coin-flip game, or could be accurately described with the same equation with which we would describe particle diffusion. It makes the maths easier, and it also gives us a satisfying sense of understanding and mastery over an uncertain world. But this sense of understanding and mastery is an illusion.

The coin flip is an inapt metaphor. Financial markets are not a random walk. We know this because, while you could flip coins from now until the end of time, you will never come across a 10-sigma coin-flip event. But, in the financial markets, 10-sigas happen all the time. This is not possible if the random walk obtains.

More importantly, in the financial markets it is the 10-sigma events that represent the vast majority of the cumulative impact in the distribution. Though the events within a 2.33-sigma range are far more numerous, they are essentially irrelevant from a risk/return perspective. A risk methodology that handles the 2.33-sigma events but breaks down on 10-sigma events is not a risk methodology at all.

### **The stock market versus blackjack**

In the real world, the practical, cumulative effect of non-defined rules and non-discrete iterations is to create wild spikes in variance, spikes that we would never see in a casino or while flipping coins, spikes of the kind that wiped out LTCM.

In the casino, because the rules are well defined, we can calculate a precise standard deviation and determine the odds on the craps table of, say, someone rolling snake-eyes 100 times in row. Because of the structure of the game, we can safely assume a perfectly normal distribution; there is no measurement error in a casino.

In the financial markets, on the other hand, we never know the true standard deviation for an asset class, nor can we safely assume

a normal distribution of returns. The standard deviation is a moving target; the distribution of returns is unstable. The best we can do is to use arbitrarily chosen historical sample sets to take a guess.

In many cases, LTCM's models went back only three years. This gave them a portfolio-wide standard deviation of US\$45 million per day. But LTCM could just have easily chosen different historical sample sets out of recent history that would have shown a daily standard deviation of US\$200 million (Jorion 2000).

The difference between a US\$45 million standard deviation and a US\$200 million standard deviation is enormous. Using a US\$45 million standard deviation places the US\$550 million losses on August 21, 1998, and September 21, 1998, as 12.3-sigma events, something that should not occur even once over countless iterations of the history of the universe, much less twice in a few weeks. However, at a standard deviation of US\$200 million, the losses on those two days are a 2.75-sigma event, something we could expect to occur every couple of years.

The lesson here is that measurement error compounds very, very quickly when using a normal distribution (Taleb 2007). Within the VaR model, the difference between an event that should never occur over hundreds of trillions of years versus an event that should occur four or five times a decade is small enough that simply choosing different historical sample sets over the last twenty years can account for it entirely.

### **Blackjack versus cotton**

We needn't necessarily assume a perfect normal distribution into the VaR model. It is possible to assume a distribution with fatter tails, one that looks like something much closer to what we observe in reality. So-called "non-parametric" approaches to VaR are one attempt at such a solution. Any method that abandons the unsound assumption of the normal distribution represents an improvement over the standard approach. Unfortunately, such approaches nonetheless fail to resolve the deeper problems in the model.

The best way to think about the shape of a distribution is its kurtosis. A normal distribution, by definition, will exhibit a kurtosis of 3. Broadly speaking, a distribution with thinner tails will exhibit a kurtosis lower than 3, with a minimum bound at 1. A distribution

with fatter tails will exhibit a kurtosis higher than 3.

The actual observed kurtosis of the Dow from 1896 through 2011 is 23 (Table 2.3), which by itself is a strong statistical indication that assuming a normal distribution – that is, assuming a kurtosis of 3 – is a reckless act of portfolio management. One alternative approach is simply to plug a kurtosis of 23 into the VaR model and continue from there.

But simply changing the kurtosis value runs into its own set of problems. Changing the kurtosis falls back into the same trap of assuming that financial markets are analogous to blackjack or coin flips: even as it accepts that the process driving financial market returns is not identical to the process driving coin flips or casino games, it nonetheless assumes that there is a single, stable process for generating the returns series.

This assumption is false. The observed kurtosis, like all the other VaR inputs, is not stable. There is no single return-driving process with a kurtosis of 23 (Table 2.4). There is no identifiable process at all.

**Table 2.3** DJIA: 1896–2011

<b>Kurtosis by decade</b>	
1890s	9.7
1900s	7.4
1910s	43.7
1920s	19.0
1930s	9.5
1940s	7.9
1950s	8.6
1960s	9.1
1970s	4.6
1980s	70.9
1990s	8.0
2000s	11.6
<b>1896–2011</b>	<b>23.0</b>
<b>Normal distribution</b>	<b>3.0</b>

Looking at Table 2.3, we might be tempted to assume away the 70.9 figure from the 1980s, as this is heavily influenced by the single-day event of the crash on October 19, 1987. But, when you consider that the purpose of a kurtosis is to measure the statistical impact of rare events, this simplifying approach seems less logically sound.

The important point to take away from the kurtosis table is that any choice you make, whether choosing the 23.0 for the entire sample, or choosing any of the individual decades, or any combination thereof, is entirely arbitrary. There can be nothing objective about the choice. Like all inputs to VaR, it is a wild guess dressed up as mathematical rigor.

Though the data presented here is specific to the US stock market, it is important to remember that this market is not unique. As Mandelbrot has shown, these same dynamics of unstable, non-normal distributions apply equally to other markets, even those as far afield as the markets for physical commodities such as cotton (Mandelbrot 1963). No matter where you look in the financial markets, you will be hard-pressed to find a normal distribution of returns, or even a stable distribution of any kind. This is why stable distributions are the wrong way to think about risk in financial markets.

### **The global financial crisis**

The global financial crisis (GFC) of 2007–2008 highlighted some of the major problems with the VaR model. The most obvious point that came out of the crisis is that VaR is a procyclical measure; that is, when times were good, the placid markets generated low VaR figures, which encouraged firms to leverage up their risk. For a time, this increasing leverage fuelled market prices, sustaining the positive cycle. As the bull cycle progressed, the VaR figures kept dropping, giving participants the false impression that the risk in the system was decreasing, when in fact the opposite was the case. The reality was that the increasing leverage gradually increased the fragility of the overall system. As a result, when the market broke in late 2007, everything went haywire at once.

Firms typically use a one-, three- or five-year trailing VaR. Unfortunately, the period between 2003 and 2007 captured only a single, sustained bull market in nearly every asset class. There was nothing in the 2003–2007 sample that remotely suggested that the events

of 2008 were even possible, much less likely to happen in the coming year. Thus, those relying on this period in their VaR models were unprepared for the events of 2008.

The Dow's standard deviation for the period from 2003 to 2007 was about 80bp. For 2008, it was 239bp. The tripling in the standard deviation meant that a 6-sigma event for the 2003–2007 period, an event so extreme that the normal distribution predicts it should occur only once every 2 million years, in 2008 suddenly became a 2-sigma event, something the normal distribution predicts should occur every 22 days. Obviously, firms relying on trailing VaR figures to manage their risk were caught off guard by this change.

An interesting feature of the GFC is that, even if a risk manager had magically known 2008's mean return and standard deviation in advance and plugged those figures into a VaR model, the daily returns from 2008 would not have been normally distributed. Indeed, this clairvoyant version of the VaR model still would have shown two 5-sigma events in 2008, events the normal distribution predicts should occur once every 7,000 years, not twice in a single year.

This phenomenon holds for virtually any period of sufficient length in the history of the Dow. In other words, VaR doesn't fail because of our inability to select the correct historical sample. It is true that VaR's failures in 2008 were particularly egregious due to the widespread sampling of the uniquely unrepresentative period from 2003 to 2007. But it wouldn't have made a difference if the VaR modellers had plugged in the Great Depression as the historical sample (or even if the modellers had been able to predict the future): VaR still would have failed to prepare its users for what happened in 2008.

The failure is not in the application of the model but in its very concept. The distributions cannot be accurately modelled because they aren't fixed over time. Financial markets are not driven by a single stochastic process. Instead, the stochastic process is constantly changing in ways that are impossible to predict or model in advance. Risk methodologies predicated on predicting and modelling what is fundamentally unpredictable and impossible to model are the wrong approach to the problem. Our thinking about the nature of financial risk needs to be more flexible and nuanced than that.

## VARIANCE IS NOT RISK

### Two traders

Imagine a pair of options traders, a BUYER and a SELLER. The SELLER has sold the BUYER a series of options such that SELLER and BUYER hold identical, but inverse, portfolios. It is a zero-sum game: as the portfolios are marked to market, every dollar that one trader makes, the other trader loses, and vice versa.

Now imagine a risk manager at a large institutional investor, who is weighing in on the decision of whether to invest the institution's money with the BUYER or the SELLER. Naturally, the risk manager runs a VaR analysis on the two traders, assuming a normal distribution. The two traders hold inverse but otherwise identical positions. Because VaR incorporates only variance and ignores directionality, the VaR analysis of the two portfolios will produce the exact same results, no matter when the test is run. For VaR purposes, these portfolios are not the inverse of one another, but are exactly the same.

But from any commonsense perspective of risk, these portfolios are nothing alike. Because of the nature of options contracts, the BUYER's potential losses are capped to the premiums paid, but the BUYER's potential gains are infinite. The SELLER, on the other hand, has potential gains that are capped to the premiums received, but faces potentially infinite losses. In other words, the BUYER is structurally immune to blow-up risk, while the SELLER is perpetually exposed to blow-up risk. And yet any variance analysis will treat these two portfolios exactly the same.

When an extreme "tail" event occurs, the VaR figure for both strategies will rise, to reflect the increase in what VaR calls "risk", but is merely an increase in variance. Since VaR ignores directionality, it ignores the fact that "tail" events can only help the BUYER, while they can only hurt the SELLER. In this case a VaR analysis will produce the paradoxical result that the BUYER's and the SELLER's "risk" has increased in exactly the same proportion because of a variance event where the only possible outcome is that the BUYER makes money and the SELLER loses it.

For the BUYER's strategy, high variance means low risk and low variance means high risk. For the SELLER's strategy, high variance means high risk and low variance low risk. Obviously there is something problematic in using the same variance-based method

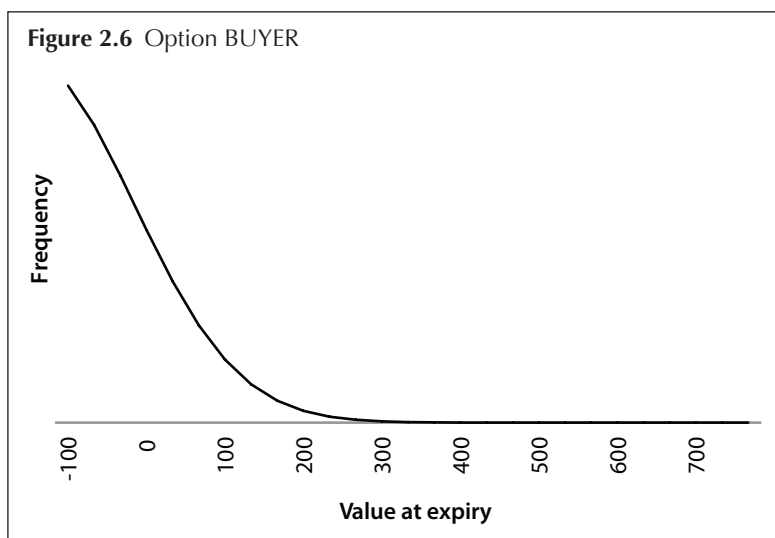
– one that assumes low variance is equivalent to low risk – to measure the risk in both. (Table 2.4)

**Table 2.4** Two traders

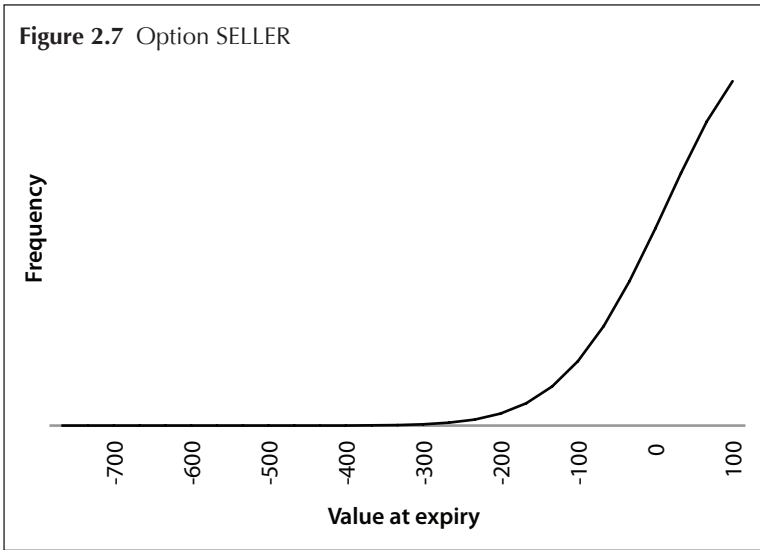
	High variance	Low variance
<b>Option BUYER</b>	Low risk	High risk
<b>Option SELLER</b>	High risk	Low risk

The fundamental assumption behind VaR is that low variance is equivalent to low risk. But what the example of the options BUYER proves is that low variance does not mean low risk for all assets. In other words, variance does not equate to risk.

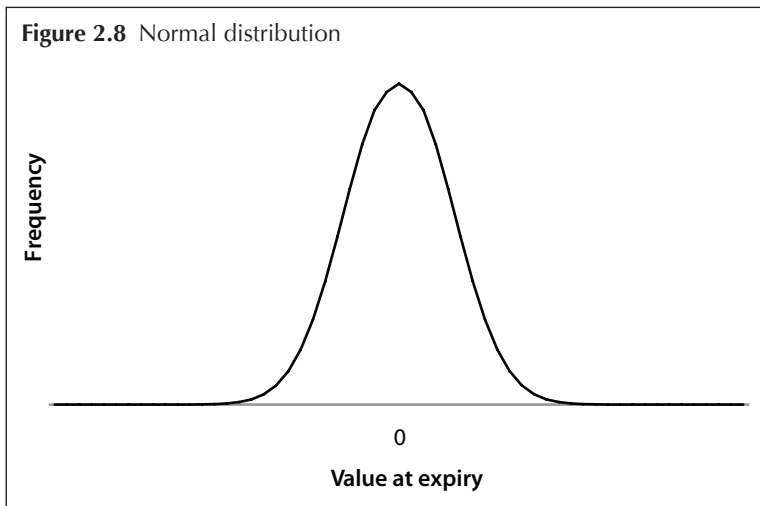
Another way of stating this is that options contracts do not conform to the normal distribution. If we stretch the time frame to incorporate the life of the contracts, we will see that option BUYERS have no left tail; their return distributions lose small amounts of money nearly all the time, but every once in a while make enormous amounts of money (Figure 2.6). Conversely, option SELLERS have no right tail. They make small amounts of money nearly all the time, but every once in a while lose enormous amounts of money (Figure 2.7). The observed distribution over the life of the contracts looks nothing like the normal distribution (Figure 2.8).







Compare the BUYER's and the SELLER's distributions (Figures 10 and 11) against the normal distribution (Figure 2.8). Is a normal distribution a fair assumption for these contracts?



**The SELLER can still make money, but VaR still doesn't measure risk**  
 This isn't to say that the BUYER will always outperform the SELLER. That will depend upon the pricing of the options and the frequency

of the extreme events that trigger the options to pay off. It is easy to imagine scenarios where, like a profitable insurance company, the SELLER prices options such that the profits made in "normal" years more than offset the losses taken when extreme events occur. But it is also easy to imagine scenarios where they do not.

The point isn't that strategies like the BUYER's that are immune to blow-up risk are always better than strategies like the SELLER's, which are prone to it. Rather, the point is that a measure like VaR can't tell you anything about their relative merits. This is for the simple reason that it can't distinguish between the two.

The relevant question is whether or not the SELLER is being adequately compensated for taking on the blow-up risk to which the BUYER is immune. But because VaR is blind to the structural differences between these two strategies, it has nothing to say on the relevant question. Indeed, it will simply say the risk in the two portfolios is always the same, no matter how much the BUYER has over- or underpaid the SELLER for the latter's options.

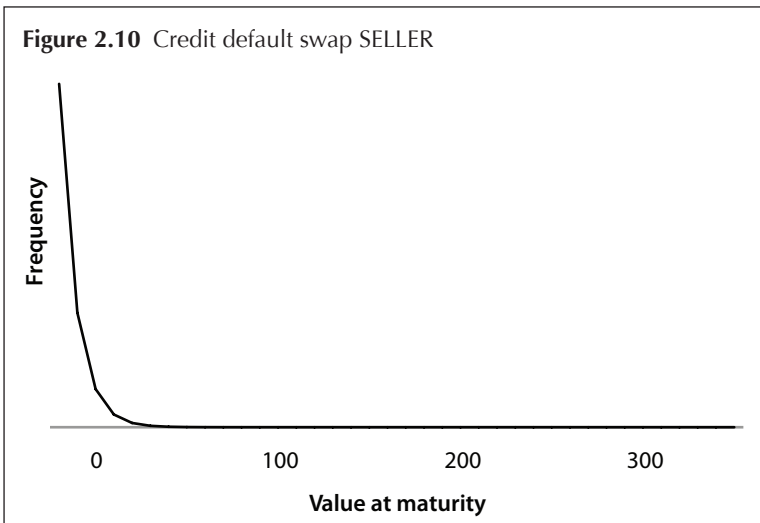
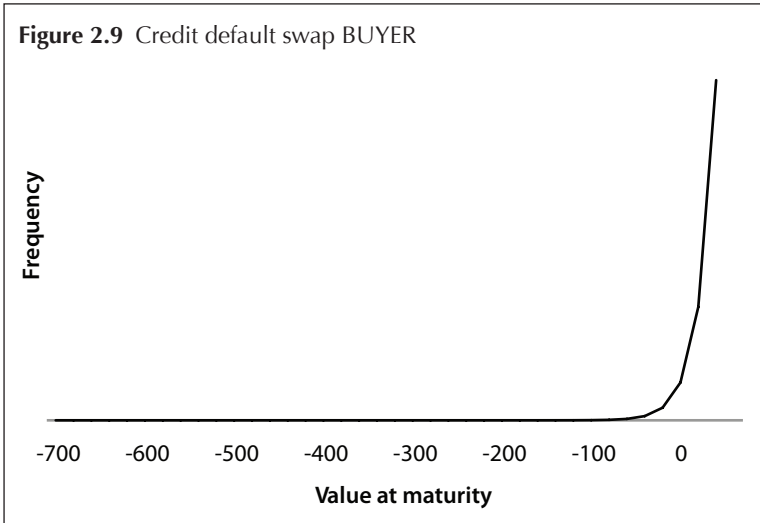
Since VaR can see only pure variance, which it considers bad, and not variance within the context of directionality, a risk manager employing VaR-based risk budgeting will systematically overweight strategies for which variance is a bad thing relative to those strategies for which variance is a good thing (for more on this, see the subsection titled "The fallacy of 'risk-adjusted' returns" below). In other words, by treating these inverse strategies as the same from a risk perspective, VaR has the pernicious effect of misleading its users into ignoring the possibilities of blow-up risk. This was the fundamental mistake that LTCM made by relying on the VaR methodology.

In short, what variance-based risk metrics consider to be low-risk strategies are merely low-variance strategies – that is, strategies that will perform well if the world proves to be not very risky. This is a dangerous bias in a risk metric.

### **Credit default swaps**

The market for credit default swaps (CDSs) demonstrates the same structural asymmetries that we see in the options market. We can repeat the BUYER and SELLER example from above, using CDSs in place of options, and the result is the same: variance and risk

are not the same thing (Figures 13 and 14). Strategies such as buying options or CDS contracts will always profit from high variance. Risk managers who equate high variance with high risk will underweight these strategies relative to strategies that profit from low variance based on a flawed understanding of what “risk” is.



### **The bond market**

The phenomenon where variance does not equal risk isn't limited to the relatively small world of options or credit market derivatives. The bond market itself is subject to it.

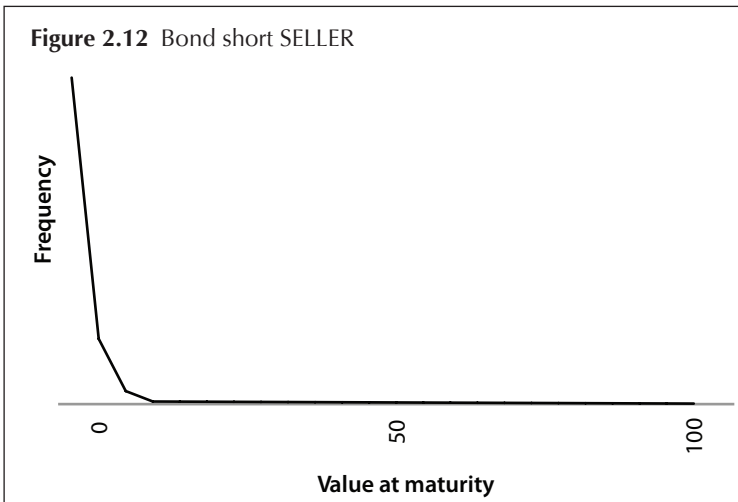
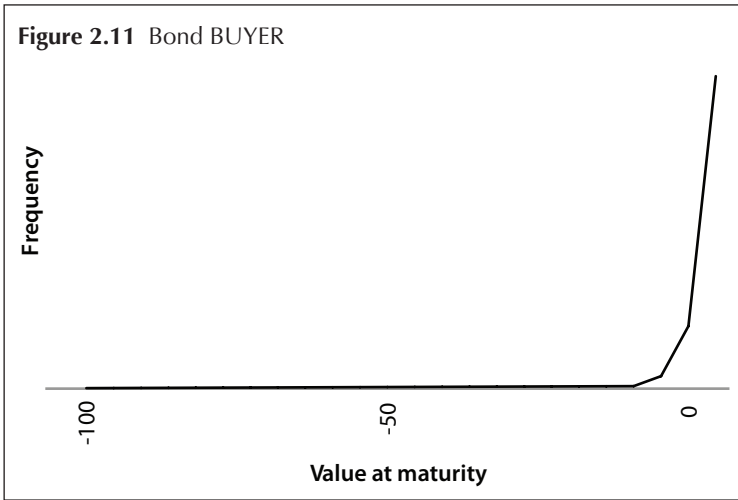
Imagine a one-year bond trading at par with a coupon of 3%. The BUYER of this bond is in a similar position to the SELLER of options or CDS contracts. The BUYER is facing a situation where his potential gain is capped – the coupon is fixed, and, for structural reasons, this bond is not going to trade beyond a price of 103 – while he is exposed to the loss of his entire investment of 100.

Thus, the bond BUYER, like the options or credit default swap SELLER, has asymmetrical exposure to extreme “tail” events (Figure 2.11). In the best possible case, an extreme event can only increase the price of the investment of 100 to 103. In the worst possible case, an extreme event can reduce the value of the investment to zero. For practical purposes, an increase in variance cannot help the bond BUYER, it can only hurt the bond BUYER.

A long bet on bonds, like a short bet on options or CDS contracts, is a bet that variance will remain low in the future. This is not the same thing as a low-risk bet. Should the trader prove wrong about future variance, with any of these positions the potential losses are many multiples of the potential gains if the trader is right.

The inverse is true for a short SELLER of bonds or a BUYER of options or credit default swaps: the potential gains are many multiples of the potential losses. Since with these strategies the maximum potential loss is predefined and small relative to the principal invested, there is no possibility of blow-up risk (Figure 2.11).

Again, this is not to say that SELLERS of bonds and BUYERS of CDSs will always outperform the counterparties taking the other side of their trades. That will depend on the pricing: are their counterparties being adequately compensated for accepting the blow-up risk? But it is to say that there is enormous difference in the risk profiles between the two strategies. A VaR analysis will obscure this enormous difference, as the inverse portfolios will exhibit the exact same variance, even as they clearly have asymmetric return relationships to changes in variance and consequently bear very different levels of blow-up risk.

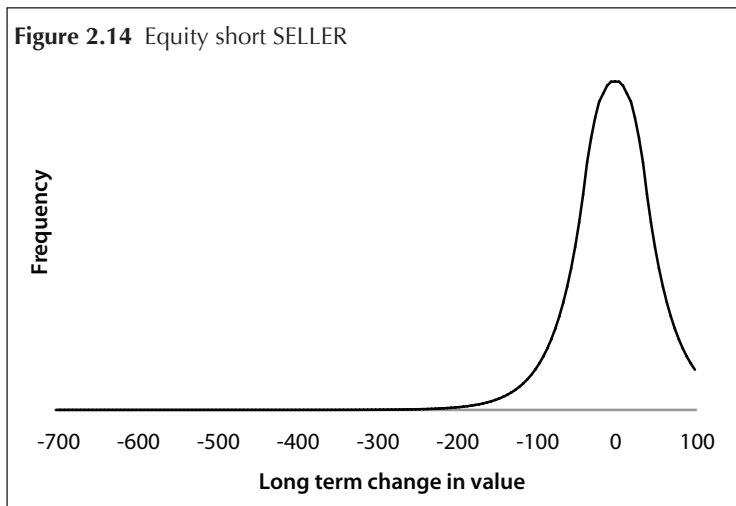
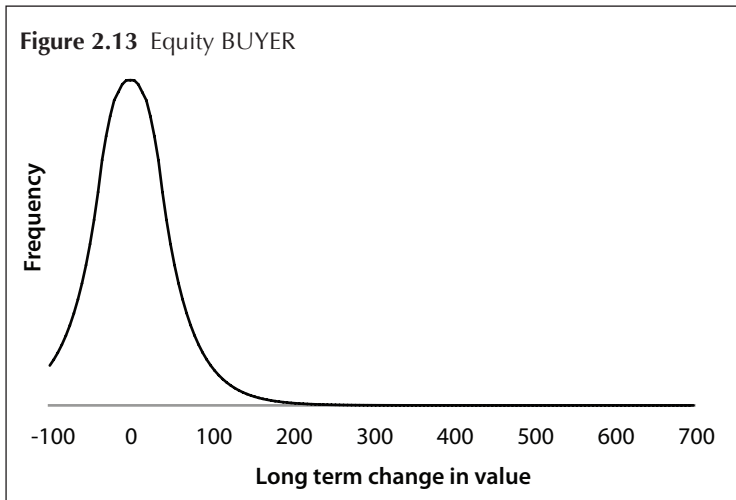


### Equities

Like the bond, CDS and options markets, the equity market is also subject to asymmetrical outcomes. As every short SELLER of equities is aware, the potential gain on a short sale is capped at 100% of the stock borrowed. The potential losses, however, are infinite (Figure 2.14). Likewise, the inverse is true for the equity BUYER: the losses are capped at 100% of the principal invested, while it is not at all uncommon to see individual equities go up 200%, 300%, 400% or more over a given period of time (Figure 2.13).

In this sense, broadly speaking the equity BUYER, like the options or CDS BUYER, is long variance. Therefore, a tool that equates higher variance with higher risk will prove misleading for equities as an asset class, just as it does for options or CDS contracts.

However, not all individual equities behave in the same way. Portfolios invested in highly leveraged business models, such as banks and insurance companies, will have more negative exposure to variance than the stock market as a whole. Conversely, portfolios invested in debt-free speculative companies gain positive exposure to extreme events.



### **The fallacy of “risk-adjusted” returns**

LTCM is a textbook case of how VaR analysis leaves the investor blind to the difference in risk profiles between the options BUYER and the options SELLER.

LTCM made much of the diversification of its portfolio, which it broke out across asset classes and geographies and countless other categories of diversification. But LTCM was sorely lacking in one form of diversification: in almost every single position in the portfolio, LTCM had taken on the role of the options SELLER, the CDS SELLER or the bond BUYER. LTCM’s bets all fitted a profile whereby they would consistently make a small amount of money in normal markets, but would lose a large amount of money if something ever went wrong. In other words, LTCM had only negative exposure to the rare event.

The reason its portfolio was built this way was that this is what its models told it would produce an optimal “risk-adjusted return.” Imagine LTCM’s portfolio taken against an inverse of LTCM’s portfolio. In any given year, the odds are very high that LTCM’s portfolio will exhibit superior “risk-adjusted” returns relative to inverse-LTCM. This is because most of the time normal markets obtain. And, as the example of LTCM showed, in normal markets – four years out of five, or nine years out of ten – LTCM will generate a 30% return at low volatility, while inverse-LTCM will produce a negative 30% return at the same volatility. To someone seeking to maximise “risk-adjusted” returns, it is obvious which portfolio they would choose.

One of the peculiarities of the “risk-adjusted” model is that, even if inverse-LTCM vastly outperforms LTCM over a full cycle, inverse-LTCM will never show good “risk-adjusted” returns. If the sample includes only normal markets, then it will show negative returns at low volatility. Even if the sample includes an extreme event, the portfolio will show high returns, but with extraordinarily high volatility.

Inverse-LTCM, like the options or CDS BUYER, will never perform well on a “risk-adjusted” basis, because each of these is a strategy that is designed to make money from high variance (“risk”). A risk methodology that rewards the minimisation of variance will always underweight such strategies. Conversely, such a methodology will always overweight LTCM-like strategies.

The variance-based concept of “risk-adjusted” returns claims that inverse-LTCM is somehow riskier than LTCM. But it is plainly not. Indeed, inverse-LTCM cannot blow up, and over a full cycle that included both 1998 and 2007–2008, it would have made an enormous amount of money. Conversely, LTCM is a ticking time-bomb, no matter how good its “risk-adjusted” returns look before the extreme event occurs.

The problem with the model is that variance is not the same thing as risk. Investors who fall into the trap of equating variance with risk will consistently find themselves building LTCM-like portfolios that are prone to blowing up. Equally problematic, users of this model will dismiss inverse-LTCM-like portfolios that are fundamentally robust to extreme events.

These tail-asymmetries are particularly important in light of the arguments made above, namely that extreme tail events are far more frequent, and carry far more cumulative weight than is predicted by the normal distribution or is commonly understood. Thus, a risk methodology that encourages left-tail exposure while discouraging right-tail exposure produces portfolios (and a financial system at large) with massive negative exposure to the inevitable extreme event. We’ve witnessed the fallout of this exact phenomenon twice in recent memory with LTCM in 1998 and the financial system at large in 2008.

VaR and “risk-adjusted” returns are a perverse way of thinking about risk. A risk-management system that encourages blow-up-prone portfolio construction is not a risk-management system at all.

## **THERE ARE NO CRYSTAL BALLS**

### **Using the past to predict the future**

There are variants of VaR that do not assume a normal distribution, instead strictly relying on past return series to predict the future distribution. This is one way around some of the many problems inherent in relying on the normal distribution. Unfortunately, the problem with this approach is the same as with the approach that assumes a normal distribution, but worse: its value is even more contingent on choosing the “right” historical sample set.

Picking the historical sample set that will most closely match future returns is no easier than predicting the future itself. The idea that a



risk manager can figure out the “right” sample set simply by thinking harder is an illusion. Financial markets do not operate like casinos; the mean, the standard deviation, the correlations, and the kurtosis are not fixed. There is no way to know the correct sample set.

It isn't only that there is no way to know the correct historical sample set. In addition, there is the much more troublesome problem that there is no way to account for events that haven't happened yet. There are instances where financial history appears to repeat. And there are instances where it does not. Those building portfolios to be robust to past crises without regard for the possibility that future crises might be different are deluding themselves about the risks they taking.

In 2001, Nassim Taleb offered the following example to illustrate the problem of naïvely interpreting past data in order to predict the future: “I have just completed a thorough statistical examination of the life of President Bush. For 55 years, close to 16,000 observations, he did not die once. I can hence pronounce him as immortal, with a high degree of statistical significance” (Taleb 2001).

New, unprecedented things happen all the time in financial markets. The collapse of the subprime market in 2007–2008 had never happened before, and neither had the convulsions in the market for CDS. There was no way to prepare for these crises based on historical modelling.

Another problem with historical modelling is survivorship bias. We model what we have data for. When we model the risk of the equity market, we model the Dow or the FTSE or some other index that has a long-running, high-quality data series. But this ignores the far more numerous indexes that have failed to leave behind high-quality data.

As Taleb has pointed out, an investor in 1900 looking to invest in three of the most promising “emerging” markets would have reasonably split the investment between the United States, Argentina and Russia. Investors in the United States did very well. Investors in Argentina and Russia did not. After 1900, the markets in both countries were subsequently nationalised; investors came away with nothing. When we use historical models to determine the risk in the US equity market, we ignore the possibility that it might go to zero for the simple reason that such a thing has never happened

before – at least not in the United States. But as the examples of Argentina and Russia show, there is no reason to believe such an outcome is impossible (Taleb 2001).

Investors in 1900 trying to understand the relative risks of investing in the United States, Argentina or Russia would have done themselves an enormous disservice by equating the risk of investing in each country with its variance in returns from 1890 to 1900. To do so would have been to grossly, almost comically, misunderstand the nature of the risks being taken.

The same principle applies today. For 150 years, the United States has been the safest, most lucrative country in the world in which to invest. But past performance is no guarantee of future results. The United States is currently running the largest deficits and is shouldering the largest cumulative debt burden in its history. It is also simultaneously engaged in one of the most aggressive monetary experiments ever attempted. How these twin phenomena will shake out is impossible to predict.

The underlying landscape is changing, as are the risks. To blithely assume that the United States' future will simply continue the trajectory of its past is reckless. Looking at variance in returns from 2000 to 2010 is no more an accurate gauge of future risk than it was for the period from 1890 to 1900. The true nature of risk is more complex than simple measures of historical variance.

### **Which past? Whose experience?**

After the LTCM debacle, Victor Haghani, one of the LTCM partners, was quoted as saying, "What we did is rely on experience, and all science is based on experience. And if you're not willing to draw any conclusions from experience, you might as well sit on your hands and do nothing" (Lewis 1999).

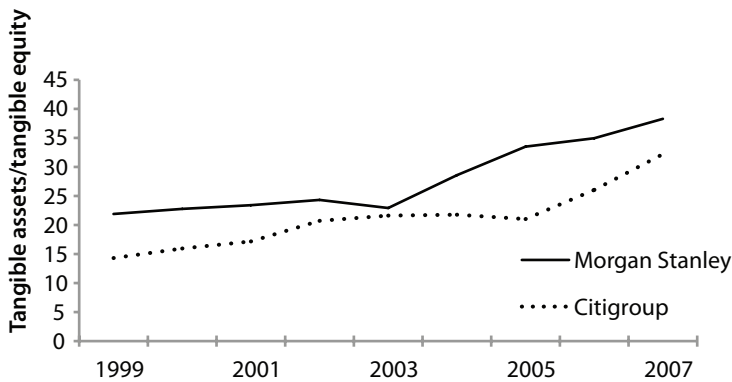
The problem with Haghani's claim is that the lessons of experience change drastically depending on which set of experience you rely. You can interpret Haghani's claim to mean that using historical measures like VaR, as LTCM did, is the only reasonable option for constructing a portfolio. Alternatively, you could study a different set of experience by counting the number of VaR-using firms that have blown up over the last 15 years. Such a study would lead to the opposite conclusion: that VaR is not a very effective system of

risk management.

Studying the past is imperative in the practice of risk management, but the naïve, uncritical use of past data creates more problems than it solves. These problems are compounded by an approach that arbitrarily imposes a theoretical tool, such as the normal distribution, that has empirically failed to describe actual historical returns.

A major theme of past financial history, including LTCM and the financial crisis of 2007–2008, is that financial markets are tail-driven. If we are interested in generating returns, or in protecting ourselves from losses, as all investors should be, then we should be spending a hugely disproportionate amount of our time thinking about tail events, as these are what drive cumulative returns. A risk-management system that fails to adequately account for tail events is not a risk-management system at all. Such systems are deeply misleading about the real nature risk, their seeming precision leading to dangerous overconfidence (Figure 2.15).

**Figure 2.15** The overconfidence index: leverage ratios, 1999–2007



Source: Data taken from Bloomberg; authors own composition

### The epistemology of risk management

Ultimately, VaR's most pernicious characteristic is to make what is fundamentally unknowable appear to be precisely quantifiable. It has repeatedly failed to protect its users in the past, and will continue to do so in the future, because its basic premises are faulty. To

summarise the argument so far: (1) fat tails are the heart of what drives risk and returns, not something that can be ignored; (2) variance does not equate to risk; and (3) the assumption that the future will look like the past is untenable.

However, these criticisms of VaR should not be taken as a recommendation for throwing our hands up in the air and taking a know-nothing approach to risk management. Rather, they should be taken as an admonition that VaR is too superficial a measure of risk to constitute an adequate risk-management process. Risk management is much harder than simply doing a VaR calculation.

An honest risk-management process must draw a distinction between the things risk managers know and those things they do not know. Risk managers do not know the true, forward-looking standard deviation of their portfolios. They do not know the frequency or severity of future tail events. They do not know future correlations between assets. Centring a risk-management process on pretending to know things that the risk manager fundamentally does not know will prove to be a fruitless exercise.

A more promising approach is to focus on what risk managers know instead of on what they do not. Risk managers know the structural tail profile of each of their assets: is the asset exposed to left-tail risk, right-tail risk, neither or both? Risk managers also know a fair amount of asset-specific information that weighs heavily on the risk of individual stocks and bonds (and the derivatives derived from them): market price versus liquidation value, financial leverage, etc. These are the analytics on which risk managers should be focusing. Risk managers must also place front and centre many issues that VaR ignores, including liquidity, regulatory and political risk.

Understanding risk this way is not easy. But there is no reason why risk management should be easy. Indeed, the number of financial firms that have blown up in just the past few decades proves that it is extraordinarily hard. Investors and risk managers are far better off embracing and engaging with these difficulties, rather than pretending they can be washed over with a single VaR metric. There is no one-size-fits-all solution to the problem. Each asset is unique and we cannot simply assume that past correlations between asset classes will hold in the future.

## CONCLUSION: HOW TO PROTECT A PORTFOLIO

A sound risk-management process will (1) not rely on the false assumption of a normal distribution, nor will it rely on the false assumption of a stable distribution of any kind; (2) it will not equate variance with “risk”; and (3) it will not attempt to use the past to predict the future.

Most importantly, a sound risk-management process will place special emphasis on tail risks. Fat tails are the thing most likely to generate returns, as well as the thing most likely to blow up a portfolio. They cannot be ignored.

VaR figures approximate the risk of a portfolio during “normal markets.” But since “normal” markets constitute a tiny fraction of the observed risks, both positive and negative, this is not a useful measure. Indeed, VaR’s failure to account for tail exposures can be extremely misleading. Taken to the extreme, as in the case of LTCM, the use of the VaR methodology and the closely related metric of “risk-adjusted” returns leads to a portfolio that is “optimised” for “normal” markets, but that is especially vulnerable to tail events. Such portfolios are blow-ups waiting to happen.

The problems of VaR run deep. It isn’t only the assumption of a normal distribution that causes trouble. More fundamentally, it is the assumption that financial markets are akin to a casino game, or a coin-toss game. It is the assumption that there is a single stochastic process driving the markets, and that this process can be understood, modelled and used to make predictions about the future.

This assumption is false.

The way forward in financial risk management is a less quantitative approach, an approach that treats the markets as a qualitative problem that must be studied and analysed to be understood, not as a second-rate math problem to be definitively solved (Taleb 2007).

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