Strategy one: Buy and hold, single contract

What have I told you since the first day you stepped into my office? There are three ways to make a living in this business. Be first. Be smarter. Or cheat. Now, I don't cheat.

— John Tuld, the fictional bank CEO played by Jeremy Irons in the film *Margin Call*

Like John Tuld, I don't cheat. And I believe that consistently being first is not a viable option for futures traders, except for those in the highly specialised industry of high frequency trading. That just leaves being *smart*.

How can we be smart? First, we need to **avoid doing anything stupid**. Examples of rank stupidity include: (a) trading too quickly – slowly draining your account through excess commissions and spreads; (b) using too much leverage – quickly blowing up your account; and (c) designing a set of trading rules that assume the future will be almost exactly[11] like the past (also known as *over fitting* or *curve fitting*). During the rest of this book I'll be explaining how to avoid these pitfalls by using properly designed trading strategies.

Avoiding stupid mistakes is a necessary but not sufficient condition for profitable trading. We also need to create strategies that are expected to earn positive returns. There are a couple of possible methods we could consider to achieve this.

The first way, which is very difficult, is to find some **secret** unique pattern in prices or other data, which other traders have been unable to discover, and which will predict the future with unerring accuracy. If you're looking for secret hidden formulae you're reading the wrong book. Of course, if I did know of any secret formula I'd be crazy to publish it; better to keep it under my hat and keep making millions in easy profits. Sadly, highly profitable strategies tend not to stay secret for very long, because of the substantial rewards for discovering them.

Alternatively, to earn positive returns we can **take a risk** that most other people are unwilling, or unable, to take. Usually if you are willing to take more risk, then you will earn higher returns. This might not seem especially smart, but the clever part is understanding and quantifying the risks, and ensuring you don't take too much risk, or take risks for which the rewards are insufficient. Blindly taking risks isn't smart: it's terminally stupid. The trading strategies in this book aren't secret, so to be profitable they must involve taking some risks that most people in the market aren't comfortable with.

The advantage of a risk taking strategy is that human beings' risk preferences haven't changed much over time. We can check these strategies have worked for long historical periods, and then be pretty confident that they will continue to work in the future. They tend not to be as profitable as secret strategies, but this is also an advantage because the fact of their already being known about, and existing for a long period of time already, means they are unlikely to be competed away in the future when other traders discover them.

What sort of risks do we get paid for? The list is almost endless, but for starters the most well-known risk in financial markets is equity market risk, which is informally known in the financial markets as *beta (β)*. Equities are almost always riskier than bonds, and certainly riskier than bank deposits, and thus we would expect them to earn a higher return.

Economists usually assume we can buy the entire stock market, with portfolios weighted by the market capitalisation of every company. In most countries it's not realistic to buy every listed stock, but you don't have to, because the largest firms make up the vast majority of the market. If you want to earn US stock market beta, then you could just buy all the stocks in the S&P 500 index of the largest firms in the US, spending more of your money on shiny gadget maker Apple (at the time of writing, the largest stock in the S&P 500 with around 6.4% of the index weighting) and only a tiny fraction on preppy clothing outlet Gap (just 0.013% of the weighting).

However, buying 500 stocks is going to be an expensive and time-consuming exercise. You will also have to spend more time and money adjusting your exposure whenever stocks are added to and removed from the index.[12] There is a much simpler way, and that's to buy a futures contract that will provide exposure to all the stocks in the S&P 500.

This is our first trading strategy, and it's the simplest possible:

Strategy one: Buy and hold a single futures contract.

Initially we'll focus on the S&P 500 future as a way to get exposure to – and be rewarded for – equity market risk. Later in the chapter I'll explain how and why we'd want to buy and hold other kinds of future from different asset classes. We'll also learn about some important concepts in futures trading:

- Futures multipliers, tick size and tick value.
- Expiry dates and rolling.
- Back-adjusting futures prices.
- Trading costs.
- Calculating profits.
- Required capital.
- Assessing performance.

Multipliers, tick size and tick value

As you might expect, given the S&P 500 is a US index, the primary exchange where you can trade S&P 500 futures is also in the US: the Chicago Mercantile Exchange (CME). Perusing the CME website, we can see that there are two sizes of S&P 500 future, defined as follows:[13]

- The *e-mini* future (symbol ES), with a 'contract unit' of $50, and a 'minimum price fluctuation' of 0.25 index points = $12.50
- The *micro e-mini* (symbol MES), with a 'contract unit' of $5, and a 'minimum price fluctuation' of 0.25 index points = $1.25

The 'contract unit' defines the relationship between the price and value of different futures contracts. Let's imagine that the S&P 500 is currently at a level of 4,500 and we decided to buy a single contract – the smallest possible position. The price rises by 45 to 4,545. What is our profit? A buy of the e-mini would have resulted in a profit of 45 × $50 = $2,250. Whereas if we had bought the micro contract there would be an extra 45 × $5 = $225 in our account.

To calculate our profit we *multiply* each $1 rise in price[14] by the 'contract unit'. Hence, rather than contract unit, I prefer to use the term futures **multiplier**.[15] Another way of thinking about this is as follows: Buying one contract is equivalent to buying stocks equal in value to the price (4,500) multiplied by the contract unit. For example, if we were using the e-mini we'd have exposure to 4,500 × $50 = $225,000 worth of S&P 500. You can easily check this assertion: a 45 point change in the price is equal to 45 ÷ 4500 = 1%, and 1% of the notional value ($225,000) is $2,250, which is the profit for holding the e-mini that we've already calculated. I call this quantity the **notional exposure per contract**:

Here the notional exposure and multiplier are in US dollars, but in principle we could convert a notional exposure into any currency. I define the **base currency** as the currency my account is denominated in. Then:

The FX rate is the relevant exchange rate between the two currencies. We'll need this formula if our trading account base currency is different from the instrument currency. As an example, if I'm a UK trader trading the S&P 500 e-mini then the relevant FX rate would be USD/GBP. At the time of writing the FX rate is 0.75, hence my notional exposure is:

Now, what about the 'minimum price fluctuation'? Simply, the futures price cannot be quoted or traded in smaller units than this minimum. Hence a quote of 4500.25 would be okay for the e-mini and micro contracts with a minimum fluctuation of 0.25, but a price of 4500.10 would be forbidden.

As minimum price fluctuation is a bit of a mouthful, I will instead use the alternative term **tick size**. Multiplying the minimum fluctuation by the futures multiplier gives us the **tick value**.

In the case of the e-mini contract this is 0.25 × $50 = $12.50.

The decision as to which of the two S&P 500 futures we should trade is not entirely straightforward, and I will answer it in a subsequent chapter. For now we'll focus on the smallest micro future, with a futures multiplier of $5, a tick size of 0.25, and a tick value of 0.25 × $5 = $1.25.

Futures expiries and rolling

Having decided to trade the micro future, we can check out the order book to see what there is available to buy. An order book[16] is shown in table 1, with some other useful statistics.

Table 1: Order book (i) for S&P 500 e-mini micro futures, plus volume and open interest

	Bid	Offer	Mid	Volume	Open interest
Sep 2021	4503.25	4503.50	4503.375	119,744	123,856
Dec 2021	4494.00	4494.25	4494.125	6,432	6,073
Mar 2022	4483.25	4483.75	4483.500	12	227
Jun 2022	4485.25	4486.25	4485.750	0	4

Order book as of 9th September 2021. Mid is average of bid and offer.

S&P 500 micro futures expire on a quarterly cycle in March, June, September and December. The current **front month**, September 2021, is the most liquid. It has the highest *volume* traded today (just under 120,000 contracts), and also the largest number of open positions (*open interest* of over 120,000 contracts). But this future will expire on 17th September, in just eight days. It hardly seems worth bothering with the September contract: instead we will purchase the next future, December 2021, which is already reasonably liquid. With a market order we will buy at the offer, paying 4494.25.

Trading costs

Sadly brokers and exchanges don't work for free: it costs money to buy or sell futures contracts. I split trading costs into two categories: **commissions** and **spread costs**. Commissions should be familiar to all traders, although many equity brokers now offer zero commission trading. For futures, we normally pay a fixed commission per contract. For example, I pay $0.25 per contract to trade micro S&P 500 futures and $2 for each e-mini. These are pretty good rates for retail traders, but large institutional traders can negotiate even lower commissions.

Additionally we need to pay a spread cost, which is the value you are giving up to the market when you buy or sell. I define this as the difference between the price you pay (or receive if selling) and the mid-price that you'd pay or receive in the absence of any spread between bid and offer prices. Later in the book I'll discuss how to avoid or reduce your spread costs, but for now I assume we have to pay up every time.

In table 1 we can't get the December future for the mid-price (4494.125). Instead we lift the offer at 4494.25, for an effective spread cost of 4494.25 − 4494.125 = 0.125. If we were selling instead and hit the bid we would receive 4494.00, again for a spread cost of 0.125. The spread cost is the same, regardless of whether we are buying or selling. It has a value of 0.125 × $5 = $0.625 for the single contract we trade.

Another way of describing this is as follows: **if the bid/offer is one tick wide**,[17] the spread cost is half of this, and thus **the value of the spread cost is half the tick value** (half of $1.25, or $0.625). The total cost here is $0.25 commission, plus $0.625 in spread cost, for a total of $0.875. Of course, if the bid/offer was two ticks wide, then the spread cost would be one unit of tick value, and so on.

This is applicable for orders which are small enough to be filled at the top of the order book in a liquid market where spreads are at their normal level. Large institutional traders will usually pay higher spread costs and will need to consider their market impact.

Now, we can hold December 2021 for somewhat longer than September, until 17th December to be exact. However, this is supposed to be a buy and hold strategy: equities are expected to go up, but only in the long run. If we want to continue being exposed to the S&P 500 then we're going to have to *roll* our December 2021 contract into March 2022, at some point before 17th December.

We roll by selling our December contract, and simultaneously buying the March 2022 contract. Subsequently, we're going to have to roll again in March 2022, to buy the June contract. And so on, until we get bored of this particular strategy.

This question of which contract to hold, and when to roll it, is actually pretty complex. For now, so we don't get bogged down in the detail, I will be establishing some simple rules of thumb. In Part Six of this book I'll explain in more detail where these rules come from, and how you can determine for yourself what your rolling strategy should be. For the S&P 500 the specific rule we will adopt is to **roll five days before the expiry of the front month**. At that point both the front and the second month are both reasonably liquid.

How will this roll happen in practice? Well, let's suppose that we bought December 2021, which expires on 17th December. Five days before the expiry – 12th December – is a Sunday, so we roll the next day, 13th December 2021. The order book on 13th December is shown in table 2.

Table 2: Order book (ii) for S&P 500 e-mini micro futures, plus volume and open interest

	Bid	Offer	Mid	Volume	Open interest
Dec 2021	4706.25	4706.50	4706.375	119,744	123,856
Mar 2022	4698.00	4698.25	4698.125	64,432	35,212
Jun 2022	4690.50	4691.00	4690.750	12	227

Order book as of 13th December 2021. Mid is average of bid and offer.

We need to close our December 2021 position, which we can do by hitting the bid at 4706.25. So that we aren't exposed to price changes during the roll, we want to simultaneously buy one contract of March 2022, lifting the offer at 4698.25. On each of these trades we'd also be paying $0.25 commission, and also paying the same $0.625 spread that we had on our initial entry trade.

Alternatively, we could do the trade as a **calendar spread**, so called because we're trading the spread between two contracts of the same future but with different expiries. Here we do the buy and the sell as a single trade, most probably with someone who is also rolling but has the opposite position. With luck we can do a spread trade for a lower spread cost[18] and it would also be lower risk since we aren't exposed to movements in the underlying price. For now I'll conservatively assume we submit two separate orders, but I will discuss using calendar spreads for rolling in Part Six.

Time for some tedious, but important, calculations. The profits and losses so far from the buy and hold trading strategy can be broken down into a number of different components:

- The commission on our initial trade, $0.25.
- The profit from holding December 2021 from a buy price of 4494.25 to a sell of 4706.25: 4706.25 − 4494.25 = 212, which in cash terms is worth 212 × $5 = $1,060.
- The commission on the part of the roll trade we do to close our position in mid-December, $0.25.

Subtracting the two commission payments from the profit we get $1,059.50 in net profits. If we continue to implement the buy and hold strategy, we'd then have:

- The commission on the opening part of our roll trade in mid-December, $0.25.
- Any profit or loss from holding March 2022 from a purchase price of 4698.25 (which is not yet known).
- The commission on both parts of our next roll trade, rolling from March to June.
- Any profit or loss from holding June 2022 from its purchase price, whatever it turns out to be.
- The commission on the next roll trade.
- And so on.

We can break these profits and costs down a little differently as:

- The spread cost ($0.625) and commission ($0.25) on the initial trade: $0.875.
- The profit from holding December 2021 until we close it, as it goes from a mid of 4494.125 to a mid of 4706.375 (we can use mid prices here, since the spread cost is being accounted for separately): $1,061.25.
- The spread cost and commission on the closing part of the mid-December roll trade: $0.875.

Notice that if I subtract the commissions from the gross profit I get the same figure as before: $1,059.50. If we continue with the strategy we'd earn:

- The spread cost and commission on the opening part of the mid-December roll trade.

- The profit from holding March 2022 until we close it, as it goes from a mid of 4698.125 to wherever it ends up.
- The spread cost and commission on the subsequent roll trade.
- And so on.

The terms in this second breakdown can be summed so that the profits (or losses) from *any* futures trade can be expressed as:

- The costs (commission and spread) on the initial trade, and any other trades which aren't related to rolling (there are none for this simple buy and hold strategy, but this won't usually be the case).
- The costs (commission and spread) on all our rolling trades.
- The profit or loss from holding the different contracts between rolls: calculated using *mid* prices.

This seemingly pedantic decomposition of returns is *extremely* important. As I will demonstrate in a moment, it is absolutely key to dealing with the problem of running and testing trading strategies on futures contracts that, annoyingly, keep expiring whilst we're trying to hold on to them.

Back-adjusting futures price

Suppose we now want to test the S&P 500 buy and hold futures trading strategy. We go to our friendly futures data provider,[19] and download a series of daily closing prices[20] for each contract expiry date. Later in the book I'll look at faster trading strategies that require more frequent data but initially I test all strategies on daily data.

We're now ready for the process of *back-adjustment*. Back-adjustment seeks to create a price series that reflects the true profit and loss from **constantly holding and rolling a single futures contract, but which ignores any trading costs**. We'll consider the effects of these costs separately.

Why should we use a back-adjusted series? What is wrong with simply stitching together the prices from different expiry dates? Indeed, many respectable providers of financial data do exactly that. Are they all wrong?

In fact, doing this would produce incorrect results. Consider the switch from the December to the March contract shown above. When the switch happens on 13th December the relevant mid prices are 4706.375 and 4698.125 (remember, we use mid prices, as costs are accounted for elsewhere). If we used the March price after the roll date, and the December price before it, there would be a fall of 8.25 in the price on the roll date. This would create an apparent loss on a long position.

But rolling doesn't actually create any real profit or loss, if we ignore costs and assume we can trade at the mid price. Just before the roll we own a December contract whose price and value is 4706.375. We assume we can sell it at the mid-market price. This sale does not create any profit or loss, since we are trading at market value. Similarly, when we buy a March contract, we are paying the mid-market price. Although the notional value of our position has changed, as the prices are different, no profits or losses occur as a result of rolling.

All this means that, in the absence of any actual price changes, the **back-adjusted price should remain constant over the roll**. To achieve this we'd first compare the December and March price differential on the roll date: $8.25. We now subtract this differential from all the December contract prices.

The effect of this is that the December prices will all be consistent with the March prices; in particular on the roll date both prices will be the same. We can join together the adjusted December and actual March prices, knowing there will be no artificial jump caused by rolling. Our adjusted price series will use adjusted December prices prior to (and on) the roll date, and actual March prices afterwards.

We could then go back in time and repeat this exercise, ensuring that the September 2021 prices are consistent with December 2021, and so on. Eventually we'd have a complete series of adjusted prices covering the entire history of our data. Once we include costs this series will give a realistic idea of what could be earned from constantly holding and rolling a single S&P 500 futures contract.[21]

You can do this back-adjustment yourself, and I describe how in more detail in Appendix B, but it's also possible to purchase back-adjusted data. Be careful if you use third party data. Make sure you understand the precise methodology that's been used, and avoid series of data that have just been stitched together without any adjustment. Using pre-adjusted data also means that you lose the flexibility to test different rolling strategies, something I'll explore in Part Six.

Figure 1 shows the original raw futures contract prices (to be pedantic, a number of raw futures prices for different expires plotted on the same graph) for the S&P 500 with the back-adjusted price in grey.

Figure 1: Back-adjusted and original prices for S&P 500 micro future

Notice that the original prices and the back-adjusted price are not identical, although the lines precisely overlap at the end. This will always happen: by construction,[22] the adjusted price will be identical to the final set of original futures prices. Initially, the back-adjusted price is lagging below until around 2008, and then it begins to outpace the original prices. This effect is even clearer if we plot the difference between the two series, in figure 2.

Figure 2: Difference between back-adjusted and original futures price for S&P 500

Ignoring the weird noise in the plot (which is due to differences in roll timing and data frequency), there is a clear pattern. Before 2008 we mostly lost money from rolling the contract, as the adjusted price went up more slowly than the original raw prices. After 2008, we usually earned money.

Let's think a little more deeply about what the different price series are showing. An S&P 500 index value just includes the price. This series doesn't include dividends.[23] If we include dividends, we get a **total return** series:

Now for the futures. Through a no-arbitrage[24] argument, we know that the futures price at any one time is equal to the spot price of the index, plus any expected dividends we will get before the future expires, minus the interest we would pay to borrow money for buying stocks. This is known as the **excess return**:

This extra component of excess return over and above the spot return is also known as **carry**:

For the S&P 500 the carry was negative until 2008, because dividends were lower than interest rates. Hence the adjusted price was underperforming the raw futures price, as shown in the downward slope in figure 2. Subsequent to that, on the back of the 2008 crash and recession there was a massive reduction in interest rates. Dividends were also reduced, but they did not fall by as much.

With dividends above interest rates after 2008, carry went positive. As a result the line begins to slope upwards in figure 2, as the adjusted price returns were higher than the spot price. This upward trend was briefly interrupted from 2016 to 2019 when the Fed raised interest rates, but then resumed with a vengeance during the COVID-19 pandemic when rates were hurriedly slashed. Later in the book I'll discuss how we can construct a trading strategy using carry. For now, the important point to remember is that **an adjusted futures price includes returns from both spot and carry.**

Note that the adjusted futures price is *not* a total return series. The adjusted price is the cumulated *excess* return, which has interest costs deducted. When we buy futures, we are able to earn additional profits from interest paid on any cash we were holding in our trading account (to cover initial margin payments[25] and potential losses).

Because the amount of cash in any given trading account can vary dramatically, depending on the leverage you want to operate at, it's difficult to calculate exactly what we could expect in additional profits from interest on cash held. So I won't be including interest on cash in any calculations. Hence **all profits shown in this book will be for excess returns only.**

Measuring the profits from a trading strategy

We're now in a position to calculate exactly what profits we could have made from the buy and hold strategy.

Given a series of positions in contracts, N_t (where a positive number means we are long, and a negative is short), and a series of back-adjusted prices, P_t, the return in *price points* for time period t is:

For the simple buy and hold strategy where our position N is always one (a single contract), our cumulative return in price points will be equal to the change in price over the full period that we are trading (from $t = 0$ to $t = T$):

To work out our returns in dollars, or whatever currency the relevant future is priced in (the *instrument currency*), we'd multiply by the futures multiplier:

Once again, for the simple buy and hold strategy, our cumulative return in currency terms will be equal to the change in price over the full period that we are trading, multiplied by the futures multiplier. Finally, to convert this into the currency our account is denominated in (the *base currency*), we'd multiply by the relevant exchange rate:

As an example, suppose we're UK traders investing in the S&P 500 micro future, we have a long position on ($N_t = 1$, for all t), and the price goes up from 4,500 to 4,545 over a single day. With the multiplier of $5, and assuming an FX rate of $1 = £0.75:

Summing up the values of R^{base}_t over time will give us our cumulative profits from holding a single futures contract, or indeed for any trading strategy for which we've been able to calculate a series of historic positions. The cumulative return series for a US dollar trader holding the S&P 500 micro future is shown in figure 3. Incidentally, these cumulative return series are also known as **account curves**.

This is our first **backtest**: a test of a trading strategy using historic data.

Figure 3: Account curve (cumulative return in US$) from holding a constant long position in a single micro S&P 500 contract

This plot is identical to the back-adjusted price series in figure 2, but the *y*-axis shows different values as we have effectively multiplied the price by the futures multiplier, and started at a base of zero. We end up earning a total profit of over $200,000.

Bear in mind that these profits do not allow for the costs of *rolling* our position. We can easily get a rough idea of the likely costs. The backtest is around 40 years in length, rolling four times a year, with a total cost calculated above of $0.875 × 2 = $1.75 on each roll. This gives a grand total of 4 × 40 × $1.75 = $280. That doesn't make much of a dent in our total profit. Feel free to deduct another two chunks of $0.875

for the initial purchase and final closing trade if you're feeling pedantic! But you could well ask if it was really realistic to assume that we would have paid precisely $1.75 every single time we rolled, even way back in 1982? This is a question I will address in a later chapter.

Remember, these are *excess* returns. We would have made additional returns from earning interest on the cash in our account, especially earlier in the testing period when interest rates were usually at least 5%, and sometimes occasionally over 10%. But receiving interest on deposits isn't part of our trading strategy, and the amount earned will depend on our leverage. We should ignore any interest payments to get a purer measure of performance.

Backtesting

It's fairly easy to define a backtest: it's a test of a trading strategy using historical data. But that still leaves some important questions unanswered. Firstly, **what exactly is the point of doing a backtest?**

We run backtests for a couple of different reasons. The first, which is what most people think about, is to make decisions about how we should trade in the future. Decisions such as: which trading strategy should we use? Which instrument(s) should we trade? How should we allocate our risk across strategies and instruments? More often than not, those decisions are made by looking just at outright or risk adjusted performance: which of these alternatives is more profitable?

The second reason for backtesting, which is often overlooked, is to get an idea of the *behaviour* of a given trading strategy. How often does it trade? How expensive are its trading costs? How much leverage does it use?

How should we backtest?

Backtests have a dual nature. They run over historical data, so they show us what would have happened in the *past*. But we then use their results to make decisions about what to do in the *future*. There is an inherent contradiction here. Should we make our backtests as realistic as possible, reflecting what we could have actually achieved in the past. Or should we create something that would be a better guide to how we will trade in the future?

For example, suppose that you run a backtest to decide whether to use strategy A or strategy B, and you have data back to 1970. With the benefit of hindsight strategy B is much better than A, but at the start of the backtest you have no information about whether strategy A or B was superior. To make it a realistic simulation of the past, you would have to include both strategies in the backtest until you had evidence, based only on backward looking information, that strategy B was better.

This means your backtest will begin as a blend of A and B, and gradually morph into containing only strategy B. The returns from that hybrid strategy would be a realistic indication of what someone starting in 1970, with no forward-looking information, would have been able to achieve.

But this weird concoction of strategies is not what you are going to trade now! Instead, you will be trading strategy B without a hint of A to be seen. If you want to understand or calibrate the likely behaviour of your trading strategy, then you would be better off just backtesting strategy B, once you had determined it was the better option.

This is a common approach, but it is fraught with danger. The backtested returns from just strategy B will, by definition, be higher than the more realistic figures you would have got from a purer backtest blending A and B with no forward-looking information. Testing only strategy B is pejoratively known as *in sample*.

We have made decisions with the full knowledge of what occurs in the future, such as selecting B over A. These decisions are known as *fitting*, hence what we have done here is *in sample fitting*.

To an extent this is unavoidable; if we want to understand whether we should trade A or B then we need to test both. If we subsequently want to understand the behaviour of the strategy we have selected, then we will need to examine the returns and trading patterns of the chosen strategy, which will be 100% invested in strategy B. As long as we bear in mind that the returns achieved are almost certainly unrealistically high, then not too much harm has been done.

However, there is another trap for users of in sample backtests, and that is the curse of *over fitting*. It is fine to choose B over A, but only if there is sufficient evidence that this is the correct decision. In practice it's unlikely that our hypothetical strategy B is so much better than strategy A that we would be justified in dropping A entirely. This is because financial data is noisy, and almost never has sufficiently clear patterns that we can be significantly confident about such decisions.

To take an extreme example, suppose your backtest suggested that the day of the year with the highest returns was 26th January. Would it make sense to sit on your hands for the rest of the year, and only trade on that single day? Of course not, that would be absurd. But plenty of traders are prepared to, for example, only trade the EUR/USD future purely because it has the highest returns in their backtest.

(A more subtle problem with backtests is that there are some aspects of the past that we know for sure will not be repeated. As an example, the US Fed fund interest rate has fallen from over 10% in 1980 to 0.25% as I'm writing this paragraph. This significantly flattered bond performance, but it would clearly be a serious mistake to allocate our money only to strategies which had a bias to being long US bond futures. In later strategies I'll explore how we can try and avoid this problem by extracting the effect of these trends from performance statistics, but for now it's a serious concern.)

By only trading strategy B there is a serious danger that we have extrapolated the past blindly into the future, putting all our eggs into a single basket that is balanced dangerously on the edge of a cliff. Just because B has done a little better in the past, does not give us any guarantee that B will outperform A over some period in the future. Even if B is a fundamentally better strategy, the laws of chance mean that it could very well underperform A in the next few years.

With an understanding of statistical significance, a properly designed backtest would begin with a blend of A and B, and then gradually reallocate capital to the better strategy as more information about their relative performance was discovered over time. The most likely outcome would be that there would still be allocations to both A and B, but with more in B.

Going forward, you would want to trade both A and B in the final proportions you obtained in the backtest. And to test and understand how this mixture of A and B behaved, you would probably run a second test with those proportions fixed. But again, the returns from this backtest would be overstated, although not by as much as a backtest only of strategy B. Still, by continuing to trade both A and B you have limited the dangers of in sample fitting to a minimum: hedging your bet on B with an allocation to A. This approach is more *robust* than the alternative of just trading B.

How should we use backtest results?

Good traders will use backtest results when their results are significant, but also consider other information. For example, it makes sense for a long position in volatility futures to return a negative return over time, for reasons I will discuss later in this chapter. We can trust this result in a backtest, and expect it to be repeated in the future. In contrast, where backtest results can't be logically explained, there is a good chance it is *data-mining*: pure luck, and not to be trusted regardless of the statistical significance.

In this book I'll show you the results of my backtests, but I will also suggest what would be a robust course of action to take, given the statistical significance of my analysis. Of course you are free to ignore my suggestions, for example by taking decisions that assume the backtested results are a perfect guide to the future. Just be aware that there are potential dangers in taking this approach.

Please also bear in mind that the results of *any* backtest will be potentially overstated, if they include decisions made with information that could not have been known in the past. Where possible my backtest results include decisions made without the benefit of hindsight by using automated fitting techniques that are only allowed to see past data, but you should always assume that backtested results overstate what we could really achieve in the future, no matter how carefully they have been constructed.

Capital

Quoting profits in US dollars is generally frowned upon in finance, as they are meaningless without any context, although this message hasn't got through to the leagues of Instagram trading influencers who hook you in with inflated claims of making a guaranteed income of $500 per day. Making $24,000 in just over 40 years, as we do in figure 3, is fantastic if you start with just $100. It's less impressive if you started with $1 million. The *y*-axis in figure 3 starts at zero dollars, but we couldn't actually have run this trading strategy with no money.

How much trading capital would we actually have needed to make these profits?

If we weren't trading futures, and had no access to leverage, the answer seems straightforward. The S&P index at the start of the testing period was around 109. To get the equivalent exposure that we had with micro futures, we'd need to have bought 109 × $5 = $545 worth of the underlying stocks. Nowadays, with the index at around 4,500, we'd need $22,500.

However, one of the more useful attributes of futures markets is that we don't need to put the entire exposure value up in cash – only what is required for initial margin. Right now, to buy one micro future only requires $1,150 initial margin. Given the current notional value of a single contract (around $22,500), this works out to a potential leverage ratio of almost 20:1.

But it would be pretty crazy to buy a single micro contract with just $1,150. Things would be fine if the price went up in a straight line, without ever moving against you, but of course this will never happen. We also require additional *variation* margin to cover potential losses. Since the multiplier here is $5, for every point the index price moves against us, we'd be required to put up an additional $5.

If that cash wasn't already in our account, then there's a good chance the broker would liquidate our position unless we moved quickly to top up our trading account. How much additional cash do we need? If we were ultra cautious, then for a long position you would want to put up enough cash to cover yourself against the price going to zero. This would be equivalent to the entire notional value[26] of the futures exposure. That is extremely conservative! There are some circumstances when that might make sense, but generally you would hope that you could close your long position long before the price hit zero. But for now I am going to assume that we put up the entire current notional exposure value as capital; effectively trading without any leverage.

This will allow us to get an understanding of the performance characteristics of each individual asset. When we get to strategy two, I'll discuss how we can adjust the capital required to reflect the *risk* of a given asset.

Figure 4 again shows the cumulated profits graph, this time overlaid with the required capital. It isn't a surprise that they follow each other closely; the grey capital line is the current futures price multiplied by the futures multiplier, whilst the darker profits line is the sum of differences in the adjusted price also multiplied by the multiplier.

Figure 4: Account curve ($) and required capital ($) for S&P 500 micro futures

If we divide the profits made each day by the capital required on the previous day, then we can calculate percentage returns:

Then we get the percentage returns shown in figure 5.

Figure 5: Percentage returns from buy & hold single contract strategy in S&P 500

The scary days of 1987, 2008, and to a lesser extent 2020 are fairly clear; and should also be familiar, since this is how stock returns are normally shown. Another way to visualise our performance would be to cumulate up[27] these daily percentage returns, adding each return to the previous day's return.

Figure 6 gives quite a different picture from figure 3. When looking at dollar returns, movements in earlier years appear much smaller in figure 3. But in summed percentage terms they are quite significant. My preference is to use graphs[28] like figure 6, since it's easier to see the full range of returns throughout the history of data.

Figure 6: Account curve (cumulated sum of percentage returns) from buy and hold S&P 500 strategy

Assessing performance characteristics

Annual returns

Quoting performance figures as percentage returns is only the first step to properly evaluating the returns of our strategy. The total return in figure 6 is nearly 250%. That would be incredible over a single year, but we took over 40 years to earn that lucrative sum. We need to calculate an *average* annual return.

We could do this by measuring the return in each year, and taking an average. Alternatively we could measure the daily returns, take an average of those, and then *annualise* them. Assuming we're using the mean as our average, we'll get the same result.

To annualise daily returns, we need to multiply by the number of days in a year.[29] This is not the usual 365, the less common 366, or the approximate 365.25 (or an extremely pedantic 365.2422), since we only have returns for business days when the market is open. The number of business days per year varies depending on the year and the market you are trading but – for reasons that will become apparent below – I prefer to assume there are exactly 256 business days in a year.[30]

The average daily return for the S&P 500 strategy is 0.0235%, which if I multiply by 256 equals 6.02% per year. We could also measure the average weekly, monthly or quarterly return. But I prefer to focus only on daily returns (since we're using daily data to calculate our series of profits) and annual returns (as I find them more intuitive).

Risk and standard deviation

Futures are leveraged instruments which often have very low margin requirements. With Eurodollar interest rate futures anything up to nearly 500:1 is theoretically possible (although not sensible!). As a result we have a degree of latitude in deciding how much leverage to use. If we double our leverage, then we double our returns, but we also double our risk. So it's meaningless to talk about outright returns, rather we should discuss *risk adjusted* returns.

But it's extremely difficult to define what is meant by risk. For starters, should we use a *symmetric* or *asymmetric* measure of risk? A symmetric measure of risk treats all returns as equally risky, whether they are positive or negative. An asymmetric measure is only concerned with negative returns.

What possible logic could there be for using a symmetric measure of risk? Surely, we only worry about unexpected losses, whilst an unexpected gain is a joyous event to be celebrated? There are however a few reasons why symmetric risk makes some sense. Firstly, to get technical, if we measure our risk using all the available returns, then our risk statistic will be a more robust measure and less susceptible to occasional outliers.

Secondly, once we are using daily returns it becomes likely that we'll see both negative and positive returns: for the S&P 500, 54% of the daily returns are positive and 46% negative. If we are currently taking a lot of risk, then we're only ever a coin flip away from a pleasingly large positive return turning into a depressingly large negative return. Hence, it makes sense to treat positive and negative returns as equally risky.

Finally, when trading futures we can be both long and short, even if for now we're limiting ourselves to long positions. If we used an asymmetric measure of risk, we'd have a different measure of price risk depending on our position. That would rather overcomplicate our lives!

With that in mind, my preferred measure for a symmetric measure of risk is the **standard deviation** of returns.

Why not use drawdowns?

A very popular measure of risk is the **maximum drawdown**. This is the maximum cumulative loss experienced at any point during the backtest of a trading strategy. It's an asymmetric measure of risk, which seems to make more intuitive sense. Similarly, you could use the average return divided by the maximum drawdown as a measure of risk adjusted returns. And in fact this is a very popular measure amongst many traders: it even has a name – the 'Calmar Ratio'.

But there are a few reasons why I'm not especially enamoured of the maximum drawdown as a risk measure. There is only one maximum drawdown in a data set, so our statistics are dependent on a small subset of the data.[31] Secondly, the size of the maximum drawdown depends on the length of your data set; the largest drawdown seen over a 30 year backtest will usually be much larger than the same statistic for a single year.

Finally, using our maximum drawdown as the risk measure may give us a false sense of security, and fool us into thinking that this figure is the most we can lose. This is unlikely to be the case.[32]

We could make the measure a little more robust by using the *average* drawdown and I will also calculate this figure as it does give some insight into the returns of a strategy (to estimate this we measure the current drawdown on all the days in our data set, and then calculate the mean of those daily drawdown figures).

But for my primary risk measure I still prefer to use the standard deviation.

To calculate the standard deviation of a series of returns r_1… r_T we'd first find the mean r^*:

We can then calculate a standard deviation:

We can calculate this on an annual or daily basis, or for any other frequency. We can also *annualise* the daily standard deviation of returns, as we did for average returns. This means we can use more data (over 10,000 daily returns rather than just 40 annual returns), but end up with a more intuitive annual figure.

Under certain assumptions, which I'll come to in a second, we can do this by multiplying the daily standard deviation by the square root of the number of business days in a year. If, like me, you assume there are always 256 business days in a year then we can annualise a daily standard deviation by multiplying it by the square root of √256 = 16. This nice round number is my reason for assuming there are precisely 256 business days in every year.

If we measure the daily standard deviation of returns in figure 5 we get 1.2%, which when annualised is 19.2% per year. But if we directly measure annual standard deviation we get 17.2%. These figures are different, and not just because the actual number of business days is not precisely 256 days in every year. They are different because the 'certain assumptions' that I made are not true in practice.

The first assumption I made when annualising was that there was zero *auto-correlation:* yesterday's return has no influence on tomorrow's return. This is unlikely to be the case in practice. In financial data we often get positive auto-correlation, which is the phenomenon by which up days tend to be followed by up days, and vice versa; or negative auto-correlation when up days are usually followed by down days, with the reverse being true.

Consider an extreme situation in which we made $1 one day, and then lost $1 on the subsequent day, then made $1, lost $1, and so on; an example of perfectly negative auto-correlation. Every year we would make $0 or $1, and our standard deviation measured using annual returns would be around $1. But our daily standard deviation would be $1, or $16 once annualised. Negative auto-correlation of daily returns results in annualised standard deviation being too high.

The second assumption was that daily returns have a symmetric, *well-behaved* distribution. For example, suppose we earn $1 every day, and then on the final day of the year we either lose $364 or gain $364. Trivially, the annual standard deviation will be $364, since in half the years we break even and in the other half we make $728. However the daily standard deviation is $19.05, which when annualised comes to just $304.

These are contrived examples designed to give extreme results, and generally the annualised figure is pretty close to the value calculated by using actual annual returns, as we can see for S&P 500. It's usually better to use the annualised figure calculated with daily returns since it uses more data points for its estimation, and thus is more robust. But you should be aware that it may sometimes give misleading results.

Risk adjusted returns: Sharpe ratio

Now we have a measure of risk, we can use it to calculate risk adjusted returns. The **Sharpe ratio (SR)** is the average excess return (mean return less risk-free interest rate), divided by the standard deviation of returns:

In this book we exclusively use excess returns, so we do not need the risk-free rate:

Note that both the mean and the standard deviation need to be estimated with the same frequency. So we can divide the average daily return by the standard deviation of returns, which for the S&P 500 strategy gives a daily SR of 0.023% ÷ 1.2% = 0.0196. Or we could divide the average annual return by the standard deviation of annual returns to calculate an annual SR.

Once again, as it's better to use more data, we'd rather calculate a daily SR and annualise it. We already know we can annualise daily means by multiplying by the number of days in a year, whilst annualising standard deviations involves multiplying by the square root of the number of days. Using trivial mathematics, we can show that annualising daily SR also requires multiplying by the square root of the number of days in a year (which I assume is 256). The annualised SR for the S&P 500 is:

For the rest of this book, unless I specify otherwise, **all Sharpe ratios I quote will be annualised**.

Since we know that annualising standard deviations is fraught with potential danger, the same must be true[33] of annualising SR. But because standard deviations aren't usually too badly affected, the effect on SRs is also pretty minimal.

Measuring asymmetry: Skew

Many people are critical of the assumption of symmetric returns that underpins standard deviation, which makes the Sharpe ratio guilty by association. They prefer the **Sortino ratio** which is similar, but instead of standard deviation (the average deviation of both positive and negative returns) uses the deviation of only negative returns.

This has some value when deciding which of several trading strategies to implement, but it does not help when trying to understand the behaviour of a given strategy. If a strategy or asset has a high Sortino ratio, is it because it has a high Sharpe, or because it has a low Sharpe but has fewer negative returns?

For this reason, I prefer to use the SR,[34] but then to measure the symmetry of returns separately. There are a few different ways to do this. The classical method for measuring symmetry is with **skew**. The returns from a *positively* skewed asset will contain more losing days than for those that are negatively skewed. But the losing days will be relatively small in magnitude. A *negatively* skewed asset will have fewer down days, but the losses on those days will be larger.

Buying insurance on your house or car is a positive skew strategy. You will experience frequent small losses (paying monthly or annual premiums) with occasional large gains (receiving payouts when you crash your car or get burgled). The insurance companies you are paying premium to will see frequent small gains on your account (receiving premiums) and occasional large losses (making payouts) – negative skew.

Right at the start of the chapter I said it was smart to take a risk that most other people are unwilling, or unable, to take. Most people strongly dislike negative skew, so taking on this risk should result in higher profits. Running an insurance firm is usually profitable, hence we'd expect negative skew to be associated with higher returns.[35] It's important to be aware of the degree of skew in a given asset. If an asset has strongly negative skew, then we know our assumptions about symmetrical returns will be way off the mark, and its price is likely to be highly unstable.

Skew can also be measured for different time periods. It doesn't matter so much right now, but we'll see later in the book that you can get very different skew figures when using daily, monthly or annual returns. Again, this is down to auto-correlation. For example, suppose we had a strategy with positive auto-correlation that consistently made money in the first three weeks of each month, but then lost most of it in the fourth week. The weekly returns would have serious negative skew, but the monthly returns would be just fine.

I'm mostly going to use monthly skew, since daily and weekly skew can be seriously affected by a couple of extreme daily returns, and annual skew does not give us enough data points for a reliable estimate. The skew of S&P 500 monthly percentage returns come in at −1.37. Negative skew of this magnitude is fairly typical of assets seen as risky, like equities.

Measuring fat tails

As well as negative skew, equities also famously have *fat tails*. A fat-tailed distribution is one where extreme returns are more likely than in the standard normal Gaussian distribution. If equity returns were Gaussian, then a six standard deviation move would occur every 2.7 million years or so. With a typical daily standard deviation for S&P 500 of 1.2%, a six standard deviation move is around 7.2%. Theoretically, we would have been *very* unlucky to see a single daily return of 7.2% or more in the last 100 years. In fact there have been around *40* such days!

How can we measure these fat tails? We could continue down the route of classical statistics, by using **kurtosis**: the counterpart of skew that measures fat tails. However, I am not keen on this for a few reasons.

Firstly, I find it quite difficult to interpret figures like 6.65 (which, as you may have guessed, is the monthly kurtosis of S&P 500 futures). Also, a single figure for kurtosis does not tell you whether you have unwanted fat left tails (unusually sizeable negative returns), or extremely pleasant fat right tails (unexpectedly large positive returns). Finally, kurtosis is not a robust statistical measure, and it will swing wildly if one or two extreme days are removed or added to a data series.

Instead I'm going to use an alternative measure of fat tails. This statistic directly measures just how extreme our large returns are compared to a normal Gaussian distribution.

The first step is to *demean* the return series, by subtracting the daily mean return from every data point. Next, we measure the *percentile* of the demeaned returns at various points. Firstly, the 1st percentile: the point at which 1% of the returns in the distribution are lower, which comes in at −3.25% for the S&P 500. Then we measure the 30th percentile (−0.28%), 70th percentile (+0.42%), and 99th percentile (+3.04%).

I've chosen the 30% and 70% percentile as they're roughly equivalent to a minus one and plus one standard deviation move. The 1% and 99% points reflect the extremities of the distribution. If you wish you could use 0.1% and 99.9% to get more extreme estimates, but then you would have fewer data points contributing to your estimate, making it less reliable. This isn't so much of a problem with the 40 years of S&P 500 data, but we might only have a few years of data for some other instruments.

The next step is to divide the first two percentiles to get a **lower percentile ratio**:[36]

Similarly we can calculate an **upper percentile ratio**:

For a Gaussian normal distribution, both of these ratios will be equal to 4.43, as it's a symmetric distribution. To get an idea of how the S&P 500 compares to a normal distribution, we divide each of the ratios by 4.43 to get a *relative* ratio:

These are rather unwieldy phrases, so for the remainder of the book I will use these abbreviated terms: **lower tail** and **upper tail**. Each of these gives us an indication of how extreme the lowest and highest returns are. **Any value higher than 1 indicates our extreme returns are more fat tailed than a normal Gaussian distribution.** To put it another way, 1% of the time with a Gaussian distribution we'd get a loss that's about 4.43 times larger than our average loss. But for the S&P 500, 1% of the time we get a loss that's more than double that, 2.16 times bigger to be precise.

Summary statistics for S&P 500

I could continue discussing performance statistics for many more pages, and for several additional chapters, but I feel the statistics we have so far are sufficient to judge the performance and risk of any given trading strategy. Here's a summary of the statistics I've calculated for the S&P 500:

Strategy: Buy and hold, single contract	S&P 500 micro future
Years of data	41
Mean annual return	6.0%
Average drawdown	−23.2%
Annualised standard deviation	19.2%
Sharpe ratio	0.31
Skew	−1.37
Lower tail	2.16
Upper tail	1.60

Buy and hold with US 10-year bond futures

We originally decided to buy and hold the S&P 500 micro future to benefit from the equity risk premium. We can earn another well-known financial risk premium from taking interest rate risk (also known as *duration* risk). We can realise this through holding bond futures, of which the US 10-year government bond is one of the most liquid.

The relevant information about the contract is shown below:

Instrument	US 10-year bond future ('T-note')
Symbol and Exchange	TN, CBOT
Futures multiplier	$1,000
Tick size	0.015625 (1/64)

Commission	$0.85
Current cost of trading, per contract	$8.6625
Delivery	Physical
Expiry months	Quarterly: March, June, September, December
Roll pattern	Hold first contract until around 25 days before expiry

The raw futures contract prices, and back-adjusted prices, are shown in figure 7.

Figure 7: Raw and back-adjusted price series for US 10-year bond futures

You may find this plot quite startling; the adjusted price series significantly outperforms the raw futures price, and has done so consistently over time. Almost all of this is due to significantly higher levels of carry.

One consequence of this high carry, and the length of time we have data for, is that the back-adjusted price is actually negative for the first few years. This is nothing to worry about, as long as we ensure our strategies aren't sensitive to negative prices. In fact, the current price of crude oil futures did actually go negative in March 2020, in response to the COVID-19 pandemic. Fortunately my trading system code had been written to be robust in the presence of negative numbers and this did not cause any computer glitches!

Magic numbers and round numbers

An unwanted side effect of using adjusted prices is that we can't incorporate 'magic' or 'round' numbers into our strategies, because market participants wouldn't be using adjusted prices for their trading decisions but the actual futures prices that prevailed in the market at that time. Here's an example of one magic number strategy, based on the Fibonacci series:

Suppose the price of a stock rises $10 and then drops $2.36. In that case, it has retraced 23.6%, which is a Fibonacci number. Fibonacci numbers are found throughout nature. Therefore, many traders believe that these numbers also have relevance in financial markets.

Source: investopedia.com

I am not one of these many traders. Personally, I think Fibonacci numbers are complete hokum.

Round number strategies are marginally more plausible. Most people who are putting in stops (orders to close or open positions if some price level is achieved) will choose round numbers for their stop levels (e.g. $10 rather than $10.02). So we might expect unusual patterns of price movements nearer to round numbers (and if you are using stops, you might want to avoid round numbers!).

If you really wanted to use such strategies then you could use the current futures price rather than the adjusted price as an input into your model. But, if you do this your strategy would have a different opinion just after a roll has taken place, as the current futures price will change without anything meaningful happening in the market.

In any case, there is also debate as to whether we should use spot or futures prices with magic or round number strategies. People may think that 4,000 is an important technical level on the S&P 500, but that could equate to a less meaningful 4,013 on the future. If you're going to use magic numbers you need to decide whether the spot or futures traders are the primary driver of the market.

I prefer to use the adjusted price as it means my strategy will consistently keep its positions through a roll, and because I'm not a disciple of either magic or round number strategies.

Following the same procedure as for S&P 500 micro futures, I calculated the US$ profits from holding a single US 10-year bond future, and assumed that I had to use sufficient capital to cover my entire current notional exposure. Then I divided US$ profits into capital to get percentage returns, which are shown in figure 8.

Figure 8: Buy & hold percentage returns from a single US 10-year bond future

Compare and contrast with figure 5: this is clearly much better behaved than the S&P 500! I then cumulated up the percentage returns, which you can see in figure 9.

Figure 9: Buy & hold account curve for a single US 10-year bond future

Strategy: Buy and hold, single contract	US 10-year bond future
Years of data	41
Mean annual return	3.75%
Average drawdown	−3.90%
Annualised standard deviation	6.39%
Sharpe ratio	0.59
Skew	0.15
Lower tail	1.49
Upper tail	1.36

Being long US bonds has been an extraordinarily profitable and yet relatively safe trade over the last four decades. Of course much of that profit is down to a secular fall in US interest rates, but US bond futures have continued to earn carry even in periods when rates were flat or even rising.

We can also see that the small positive skew and relatively low percentile ratios imply that 10-year US bond returns have been reasonably close to a normal distribution.

Buy and hold with crude oil futures

I won't bore you with details of every single futures contract, but it's worth looking at a couple more instruments before I start summarising the results of the buy and hold strategy. Firstly, let's consider WTI (West Texas Intermediate) crude oil futures.

Instrument	WTI Crude Oil futures (full size)
Symbol and Exchange	CL, NYMEX

Futures multiplier	$1,000
Tick size	0.01
Commission	$0.85
Current cost of trading, per contract	$10.425
Delivery	Physical
Expiry months	Monthly
Roll pattern	Hold next December contract until 40 days before expiry

That should all be unsurprising, with the possible exception of the roll pattern. Why do I hold the December contract? Why do I roll it 40 days before expiry?

Well, commodity prices are affected by the weather, something that is not a serious issue for the S&P or US bond futures. There is a seasonal component[37] in crude oil prices, and this is true to an extent in most other commodities.

It will usually suit us to remove this seasonal component and focus on the 'true' movement in the price. So when we can, we should stick to trading a specific month in the year. I've chosen December, since it is one of the more liquid months. Unfortunately this isn't possible for every commodity future as it requires at least the next year or so of contracts to be liquid.[38] So it's not a viable option for the mini version of the WTI Crude contract, nor for natural gas futures.

As for the question of rolling so long before expiry: this is to suit a particular trading strategy that is based on the expected *carry*, and I'll discuss it in chapter ten.

Strategy: Buy and hold, single contract	WTI Crude Oil futures
Years of data	33
Mean annual return	4.03%
Average drawdown	−66.9%
Annualised standard deviation	27.7%
Sharpe ratio	0.15
Monthly skew	−0.49
Lower tail	1.81
Upper tail	1.33

Crude oil is risky, with a high standard deviation, and also subject to downward shocks (negative skew, high relative lower tail ratio). But like many commodities it will tend to perform well when macroeconomic conditions are running hot and inflation is rising. Bonds do famously badly when inflation is high, and with stocks the picture is mixed, so it seems that WTI Crude can provide us with an additional source of risk premium: an inflation hedge.[39]

Buy and hold with VIX futures

The final future I'm going to look at in some detail is the VIX future. The underlying index is effectively an aggregation of the expected volatility of all the stocks in the S&P 500, calculated using option prices. The VIX will rise when US equities are perceived to be riskier, and fall when investors feel more relaxed.

Instrument	Volatility index futures (VIX)
Symbol and Exchange	VX, CBOE
Futures multiplier	$1,000
Tick size	0.05
Commission	$0.85
Current cost of trading, per contract	$25.85
Delivery	Cash
Expiry months	Weekly and then monthly
Roll pattern	Hold second monthly contract

I focus on holding the second monthly contract for VIX. So, for example, if it was 1st March 2022, I would be holding April 2022 VIX. I will roll into May 2022 sometime in mid-March, before the March contract expires and April becomes the first contract (and May will be the second). The reasons for this are explained in Part Six, when I discuss contract selection in more detail.

Figure 10 is not a picture of a particularly dangerous roller-coaster or ski slope, as you may have initially thought, but is the cumulated percentage return series for a single VIX contract buy and hold strategy. The strategy does well in times of market crisis, most obviously in 2008 and 2020. But the rest of the time it drifts downwards, consistently losing money. In fact if we were stupid enough to hang on to this position, and keep topping up our trading account, we'd eventually lose over six times our starting capital.

Figure 10: Account curve for buy & hold strategy on single VIX contract

Strategy: Buy and hold, single contract	Volatility index futures (VIX)
Years of data	17
Mean annual return	−40.6%
Average drawdown	More than 100%
Annualised standard deviation	45.9%
Sharpe ratio	−0.88
Monthly skew	0.96
Lower tail	1.34
Upper tail	1.96

Unlike the other instruments in this chapter, we're not earning a risk premium here, but paying one out. Constantly buying[40] VIX is a bet that volatility will rise. We're effectively purchasing an insurance policy: we pay a small premium every day (the negative return), and occasionally get a big payout (as in 2008 and 2020). This is a strategy with substantial positive skew and those payouts create a nice fat upper tail. But the payouts are insufficient to overcome the drag of the premiums. In the long run, properly managed insurance companies always make money!

It could make sense to run this strategy to provide insurance for a portfolio of long equities, but not on an outright basis. Remember my guiding principle from earlier in the chapter: "It is smart to take a risk that most other people are unwilling, or unable, to take. Usually if you are willing to take more risk, then you will earn higher returns." We ought to be willing to take the risk, and *sell* rather than buy the VIX. As you might expect, the more sophisticated strategies in this book will generally have a bias towards being short VIX futures.

Summary statistics for buy and hold futures trading

This book is already too long, so I won't bore you with a detailed look at the other 99 futures in my data set. Instead let's look at some summary statistics[41] for instruments in different asset classes.[42] These are in tables 3 and 4. I will use similar tables throughout the book. Table 3 shows the financial assets: equities, volatility, FX and bonds. Table 4 has the commodities: energies, metals and agricultural (Ags) markets, plus the median across all instruments, irrespective of asset class.

Table 3: Individual performance for buy and hold across financial asset classes

	Equity	**Vol**	**FX**	**Bond**
Mean annual return	7.6%	−51.6%	−0.39%	3.2%
Standard deviation	28.9%	64.6%	15.0%	6.3%
Sharpe ratio	0.30	−0.80	−0.03	0.57
Skew	−0.78	0.73	−0.18	0.11
Lower tail	1.98	1.29	1.65	1.62
Upper tail	1.39	1.92	1.42	1.47

Table 4: Individual performance for buy and hold across commodity asset classes

	Metals	**Energy**	**Ags**	**Median**
Mean annual return	−0.94%	0.17%	−1.5%	1.35%
Standard deviation	38.3%	43.1%	28.8%	23.2%
Sharpe ratio	−0.03	0.00	−0.04	0.13
Skew	−0.50	−0.38	0.21	−0.38
Lower tail	1.86	1.72	1.54	1.74

Upper tail	1.41	1.32	1.45	1.40

We get positive adjusted returns in only two asset classes: bonds and equities. Elsewhere there are mostly small losses, except for volatility (Vol) where performance is terrible.

Now let's consider the annualised standard deviation. There is a lot of variation across asset classes. Bonds are safest, as you might expect, with average annualised risk of around 6%. FX markets are also reasonably safe. The commodity and equity markets are all pretty risky. Finally, vol is also very – and I wish I could think of a more original way of saying this – volatile.

Vol also has strong positive skew, but most other assets have negative skew. Bonds and agricultural (Ags) markets are the exception with small positive skew, whilst equities are especially nasty examples of negative skew. Equities also have distinctly fat lower tails. Most other assets aren't as bad, although none are perfectly Gaussian. Finally, bear in mind that there is considerable variation across instruments within a given asset class which these tables do not show.

Conclusion

Strategy one is the simplest possible futures trading strategy. But it still involves trading, as we have to roll our exposure. You can't just buy a futures contract, and put it under a metaphorical mattress, as you could if you bought equities. Is something so simple worth implementing?

Trading a single contract with a buy and hold strategy can be lucrative if you can somehow pick the right instrument. But that could be tricky without the benefit of the foresight we have here, and the risks are often considerable. High standard deviations, negative skew, and fat tails all lurk in the return series of most of the instruments we've considered. Although some have decent risk adjusted returns – bonds and equities in particular – it would be foolhardy to assume these will be as superb in the future.

Even if you do not trade this strategy, it's been useful to understand the performance of the underlying instruments we're going to trade. These are the raw materials we have to construct our strategies out of. We'll spend much of this book trying to improve on the statistics above: increasing return, reducing or at least stabilizing risk, nudging skew in a positive direction, and turning account killing drawdowns into survivable hiccups.

Strategy one: Trading plan

11 I do test strategies based on historic data, which is an implicit assumption that the future will look somewhat like the past. But as I shall explain in some detail it is important not to extrapolate the results of these tests blindly into the future.

12 There are quantitative techniques to make this cheaper and easier, but they are out of scope for this book.

13 There used to be three. As I started writing this book in September 2021, the CME delisted the original S&P 500 'big contract', which had a multiplier of $250.

14 There are a small number of futures which have variable futures multipliers such as the Australian bond and interest rate futures, and UK Natural Gas.

15 Readers of *Leveraged Trading* should recognise this term. In my earlier book *Systematic Trading* I use the term **block value**.

16 An order book shows all the prices at which people are willing to buy (bid) and sell (offer) the relevant future, and the quantities in which they will trade. What I've shown here is the *top* of the order book, which just shows the best prices: the highest bid and the lowest offer. I've also excluded the available quantities, since I assume we are only trading a single contract and can definitely get filled at these prices.

17 Notice that the bid-offer can only ever be expressed as integer units of tick size: 0 ticks (this is a rarely seen *choice* price, where the bid and offer are identical), 1 tick (which is what we normally see in a tight liquid market, as for the first two contract months), or multiples of a tick (the less liquid back months of March and June).

18 Calendar spreads in micro S&P 500 futures trade with a tick size of 0.05 index points. If the calendar spread was trading at 1 tick wide, we could end up paying only 0.0025 index points for the trade, worth just $0.0125 per contract.

19 Some suggested data providers appear in Appendix A.

20 Unfortunately, the micro e-mini contract was only introduced in May 2019. As I'll discuss later in the book, we need as much data as possible to test any trading strategy, and a few years isn't really enough. However, we do have data for the e-mini, and also the delisted S&P 500 'big contract' which goes back much further. Since any difference in the prices of the different futures could easily be arbitraged out, it's safe to assume that we can use S&P 500 big contract prices to backfill the prices we have for S&P 500 micro futures.

21 This is the simplest method for back-adjustment, which is known as the *Panama* method (since prices rise and fall when adjusted like ships passing through the locks in the Panama canal). There are more complex methods, but in practice they do not improve trading strategy performance, so they are not worth the effort.

22 This is a nice property of back-adjustment. An alternative method is *forward-adjustment*, where the initial adjusted price is equal to the price of the earliest contract in the data. This has the advantage of requiring less work, since we do not need to repeatedly rewrite previous data, but results in final adjusted prices that can be substantially different from the current futures price. For the strategies in this book you can use either method, and you will get the same results.

23 Some equity indices include dividends, in particular the German DAX equity index future.

24 It's not necessary to understand no-arbitrage futures pricing theory in any detail, and I won't be covering a spot versus futures arbitrage strategy in this book. Here's the elevator pitch version: suppose the futures price was higher than the cash price plus expected dividends minus the margin interest rate (the excess return on the stock). You could borrow money using a margin loan, buy a basket of S&P 500 stocks, and short the future. At expiry, any gains or losses in the stock and future would be perfectly hedged, and after paying off the margin loan and receiving the dividends you would be left with a clear risk-free profit. A similar argument explains why the futures price can't be lower than the cash price plus the expected value of dividends minus interest. You can find more detailed discussion of no-arbitrage pricing in books such as John Hull's classic work (see Appendix A).

25 Margins are cash deposited in a futures trading account to cover potential losses. An *initial margin* is required when a trade is opened, and if losses are subsequently made you will require additional *variation margin*. If you are unfamiliar with margin trading, I suggest you read my previous book, *Leveraged Trading*.

26 For a short position you'd technically need infinite quantities of cash available to cover all eventualities.

27 The normal way to cumulate up percentage returns is to take the product of $(1 + r_t)$, where r_t is the percentage return expressed as a decimal (e.g. 1% = 0.01). But charting this cumulated product would again result in a graph where the early returns were small and difficult to distinguish.

28 Incidentally, if we were to plot figure 3 with a logarithmic scale, it would look pretty similar to figure 6 but on a different scale.

29 If you're familiar with financial mathematics, this will seem wrong. We really ought to calculate the CAGR: the compounded annual growth rate (also known as the geometric mean), which assumes that returns are compounded on a daily basis. However, we're not dealing with compounded returns in this book. I'll explain why in strategy two, but for now please bear with me.

30 It's not a bad approximation: equal to 365 minus 104 Saturdays and Sundays, and a few extra public holidays.

31 To get technical for a moment, the sampling distribution of the maximum drawdown statistic shows very high variability, as it can be heavily influenced by the inclusion or exclusion of just a few days of returns.

32 There are a couple of reasons for this. One is that our data may not go back far enough. For example, we don't have equity futures data going back to the 1929 crash, and if we hadn't backfilled the S&P 500 micro data with the big contract, we wouldn't have data back to 1987 or even 2008. Secondly, it's especially dangerous to think that the worst events in the past really reflect what could possibly go wrong in the future. Someone trading S&P 500 futures in late September 1987, using data from 1975 to 1987, would have thought it was utterly impossible to lose over 20% in a single day. But then just a few weeks later the impossible happened.

33 See Lo, Andrew, 'The Statistics of Sharpe Ratios', *Financial Analysts Journal* 58 (2003).

34 There are also some technical benefits from using the Sharpe ratio (SR) and standard deviation that will become evident later.

35 Later in the book I show how to use the current level of estimated skew as the basis for a trading strategy.

36 Notice that if we didn't demean then there is a possibility that the 1% and 30% percentiles would have different signs, resulting in a negative figure here.

37 Actually the seasonality of crude oil isn't too much of an issue because it's relatively cheap to store. Seasonality is much more of a problem for natural gas, which is expensive to store, and agricultural commodities with limited shelf life.

38 This will also depend on your account size. A smaller trader might be able to trade months that aren't liquid enough for a large fund.

39 Also, oil often performs well during times of conflict, such as the 2022 Russian invasion of Ukraine.

40 If you're familiar with options, buying the VIX is effectively like buying a delta hedged straddle, or going long on a variance swap.

41 I calculated these figures by running backtests for every instrument in my data set, and calculating all the required statistics: mean return, standard deviation, SR, and so on. For each asset class I took the median value of the relevant statistic. So, for example, the SR shown for FX is the median value out of all the SRs for instruments in the FX asset class. Finally, in the final column of table 4, I took the median across all instruments, regardless of asset class. I use the median as it is more robust than the mean, which can be influenced by one or two extreme outliers.

42 Instruments include those with at least one year of data, and which meet my requirements for liquidity and cost, discussed later in the book. Examples of **Ags** (Agricultural) markets are Corn, Wheat and Soybeans. **Bonds** include government bond futures, like the US 10-year, short-term interest rate futures (STIR) such as Eurodollar, and interest rate swaps. **Equity** consists of equity indices like the S&P 500, but also sector indices in Europe and the USA, e.g. European technology. I do not trade individual equity futures. **FX** includes rates versus the dollar for G10 countries like GBP/USD, for emerging markets such as CNH/USD, and cross rates like GBP/EUR. **Metals** encompass precious metals such as Gold, industrial metals like Copper, but also Crypto: Bitcoin and Ethereum. **Energy** markets include Crude Oil and Natural Gas, but also products such as Ethanol. Finally there are the **Vol** (Volatility) markets: VIX, and the European equivalent VSTOXX. A full list of instruments is given in Appendix C.

Strategy two: Buy and hold with risk scaling

Let's review what we did in strategy one. We assumed that we had a fixed position: one contract. We then calculated a measure of how much cash – *capital* – we'd need to hold that position. This capital amount was conservatively set as equal to the notional value of the future: our position was fully funded.

But that is not how the world works! When I was working for AHL, a large hedge fund that traded futures, we didn't first decide what markets we wanted to trade, calculate the required capital for the size of positions that we wanted to have, and then go to our investors and ask them to write an appropriately sized cheque. Instead, our investors decided how much capital they were going to provide. Then it was up to us to calculate an appropriate position size.

That is the correct order: given (a) the amount of capital, decide on (b) position size. But what sort of elements would go into a calculation of appropriate position size? In this chapter I will show that the most important input into this process is the *risk* of the relevant instrument. Instruments that are riskier will usually have higher initial margin requirements, so we'd need more cash to start trading them. They also have the potential for larger losses once we're holding them, requiring more cash to cover these losses in the form of variation margin.

We saw in strategy one (in tables 3 and 4) that there is a lot of difference in risk between different futures. If an instrument has higher risk, then we'd want to hold a smaller position for a given amount of capital. In this strategy I will explain precisely how to calculate the right position for a buy and hold strategy, taking risk into account:

Strategy two: Buy and hold, with positions scaled for risk.

As well as explaining the strategy in some detail, I'll also cover the following topics in this chapter:

- Measuring risk.
- Position scaling.
- Determining the correct risk to target.
- Compounding of returns for performance evaluation.
- Calculating the minimum capital required to trade a particular future.

This is a pretty heavy chapter, with a fair number of equations. But it's vital to understand the material here before proceeding, so make sure you're happy before moving on.

Measuring the risk of a single contract

Step one in calculating position size will be to measure **how risky a single contract of a given instrument is**. Let's return to our old favourite, the S&P 500 micro future.

We need to know how risky it is to hold one contract of S&P 500. This will depend on how volatile the price of the S&P 500 future is. We'll measure this riskiness as an *annualised standard deviation of returns*. To make the maths simpler, let's assume for now that the daily standard deviation of the S&P 500 is approximately 1%, which if I annualise using the method outlined in strategy one is 0.01 ×16 = 16%.

The next step is to translate this risk into dollar terms. Here are the values we already used for strategy one:

Instrument	S&P 500 micro future
Futures multiplier	$5
Current price	4500
Current notional value	4500 × $5 = $22,500

We can use these figures to calculate our risk in currency terms, rather than percentage terms:

So owning a single futures contract exposes us to $3,600 of risk, measured as an expected standard deviation per year. Not everyone finds the standard deviation measure to be an intuitive measure of risk, so it is worth thinking about what a standard deviation of $3,600 a year implies.

To do this we have to assume that returns are well behaved, symmetric, and drawn from a normal Gaussian distribution. None of this is true in practice, which means the figures I'm about to calculate should be taken with a large bucketful of salt. In reality you should expect the downside to be significantly bigger.

With that caveat in mind, if we assume that the Sharpe ratio (SR) of S&P 500 futures is 0.3055 (roughly what it has been historically), then the average annual excess return will be:

The region of the normal distribution between the mean and one standard deviation above the mean covers around 34% of the entire distribution. As the normal distribution is symmetric the region between plus and minus one standard deviation around the mean encompasses 68% of the distribution.

So 68% of the time, our annual return will be between 1100 − 3600 = −$2,500 (loss) and 1100 + 3600 = $4,700 (profit). Alternatively, this means that we will lose more than $2,500 in any given year at least 16% of the time,[43] or roughly one in every six years.

We could also translate these figures into expectations for daily losses. But any caveats about non-Gaussian distributions are even more important for daily frequencies, and we have the usual problem that converting annual to daily standard deviations relies on some additional assumptions.

Basic position scaling

My method for calculating position size using risk is best illustrated with an example. Let's begin by making a few highly unrealistic assumptions. First suppose we have exactly $22,500 in capital. Next suppose that we're comfortable with risk on that capital of exactly 16% per year, measured in annualised standard deviation terms (I'll discuss how you'd come up with that figure in a couple of pages' time). I call this figure the **target risk**. Given those parameters, how many S&P 500 contracts would we want to own?

The answer is **exactly one contract**. We want 16% of risk on capital of $22,500, which works out to 22500 × 16% = $3,600 per year. We also know, from above, that each S&P 500 contract has risk of $3,600 per year. What an astonishing coincidence (not really)!

What if we had twice as much capital ($45,000)? Then we'd require twice as much risk (45000 × 16% = $7,200). So we'd need to buy two contracts instead of one, giving us risk of 2 × 3600 = $7,200.

Now suppose that the S&P 500 was twice as risky. With annualised risk of 32% a year, that would be equivalent to a risk on each contract of 22500 × 32% = $7,200. We'd need half as many contracts. So for capital of $45,000 and a risk target of 16% a year on that capital, equivalent to $7,200, we'd once again only need to buy a single contract.

I can formalise these results into a single equation that accounts for the possibility of different currencies. From strategy one, the notional exposure value of a single contract is:

The price should be for the expiry date we currently hold (*not* the back-adjusted price), and the FX rate translates between the two currencies. The risk of a single contract position measured as an annualised standard deviation (σ) is:

Where $\sigma_{\%}$ is the annualised standard deviation of percentage returns for the relevant instrument in the instrument currency.[44] For a given number of contracts, *N*, the risk of our entire position will be:

Next we need to specify how much capital we have, and a predetermined *target risk* (I'll explain where this comes from later), which we also specify as an annualised percentage standard deviation. Given that, we can calculate what our risk target is in currency terms:

We now set our required position risk to be equal to the risk target in currency terms:

Substituting and rearranging, we get the required position in contracts N to achieve a given target risk:

Notice that the following will all result in a larger position:

- Lower instrument risk, $\sigma_{\%}$
- A higher percentage risk target, τ
- More capital
- A lower futures multiplier
- A lower price
- A different FX rate, where the instrument currency has depreciated relative to the account currency

Let's check that this works for the surprisingly coincidental example from above:

There is an alternative formulation which I will use later in the book, which involves measuring our risk in *daily price points* rather than in *annualised percentage points*. The daily risk in price points (σ_P) is just equal to the current price multiplied by the annual percentage risk, divided by 16:

We can also calculate σ_P directly by taking the standard deviation of a series of differences in daily back-adjusted prices:

This has the advantage that it works even if the current futures price is negative, and gives us the following marginally simpler formula:

Some useful ratios

It can sometimes be helpful to use the following intuitive ratios:

The *contract leverage ratio* is the ratio of the notional exposure per contract to our trading capital. The smaller this number is, the more contracts we need to hold for a given amount of capital. The *volatility ratio* is the ratio of our target risk to the instrument risk. So if we require double the risk versus what is offered by the instrument, we'd need to hold twice as many contracts. Rearranging the original formula we get an interesting and intuitive result:

Another figure that we'll sometimes need is the *leverage ratio*. The leverage ratio is just the total notional exposure of our position, divided by our capital:

If we substitute we get the following identity:

So the **required amount of leverage will be equal to the volatility ratio**: our target volatility divided by the price volatility of the instrument we're trading. Note that this is only true if we are trading a single instrument, but this is the case for the first three strategies in this book.

Setting target risk

We’ve got all the inputs for the formula above, with one glaring exception: the target risk (τ). How should we determine what our target risk should be? There are a number of different factors we need to consider. Our target risk should be the most conservative (i.e. lowest value) from the following:

- Risk possible given margin levels. This is set by the exchange, and/or the broker.
- Risk possible given prudent leverage. This depends on your ability to cope with extreme losses.
- Personal risk appetite. This is determined by your own feelings, or those of your clients if you are trading external funds.
- Optimal risk given expected performance. This depends on the return profile of your trading strategy.

Let’s discuss these in turn.

Risk possible given initial margin levels

You can’t just buy as many contracts as you’d like, since ultimately you will be constrained by having to put up sufficient margin. Each S&P 500 micro contract currently requires $1,150 initial margin. It would be completely insane, but if we were to use our entire capital for initial margin payments we’d be able to buy the following number of contracts:

If we substitute for *N* in the formula, we can work out the implied maximum possible risk target given some margin level:

Let’s take an example. Suppose that we are trading the S&P 500 with risk of 16% a year, current price of 4500, multiplier of $5 and margin per contract of $1,150.

That’s a lot of risk! You can achieve extremely high risk targets if you use the full amount of available leverage. **For most sensible futures traders, the initial margin required is unlikely to be a constraint on their leverage.**

Risk possible given potentially large losses

Given that it’s a little crazy to use the maximum possible leverage, what is a prudent level of leverage to use? We could be fairly conservative, as in strategy one, and use no leverage at all – fully fund the strategy and set our notional exposure equal to our capital. Then we could never lose all of our money, unless the futures price went to zero or below.[45] To achieve that we’d always set our target risk to be equal to our instrument risk.

Alternatively, we could take the view that we’d be prepared to lose a certain amount in a serious market crash. Let’s suppose that a 1987 sized crash is possible, resulting in a one-day loss of 30%. Assume that we’d be relatively relaxed about losing half of our capital in such a situation. A one day 30% loss would lose us half of our capital if our leverage ratio was 50% ÷ 30% = 1.667. From before we know that with the optimal position:

So we can calculate the maximum risk target as:

And for our specific example of a 1987 crash:

Whilst it’s easy to do this calculation, assuming you can calibrate your ability to withstand large losses, it’s more difficult to work out what the expected worst return should be. Using the worst possible daily return in our historical data is a good starting point, but we'll often need some imagination to consider possible worst-case scenarios.

For example, prior to 2015 the Swiss franc:euro (CHF/EUR) FX future rarely moved more than 0.005 price units each day; about 0.5% of the price. Indeed, from late 2011 to January 2015 it hardly budged at all, reflecting the Swiss central bank's policy to stop the rate moving below a pegged level of 1.20. At this point most traders would have thought that 5% was a fairly pessimistic maximum loss; a little worse than CHF/EUR experienced in the 2008 financial crisis.

They were wrong. In January 2015 the central bank dropped the currency peg, and the exchange rate plummeted below 1.0; a move of over 0.20 price units in a matter of seconds, and about 16% of the closing price the previous day.

In retrospect it would have been sensible to look beyond the CHF/EUR market, and consider what happened in other countries when central banks dropped currency pegs. A prudent FX trader would have remembered Black Wednesday in 1992, when the British pound dropped out of the European Exchange Rate mechanism which pegged it to the deutschmark and other currencies. On Black Wednesday and the day after the pound depreciated by around 14%; showing that double digit losses are possible even in normally safe G10 currencies like the pound and the Swiss franc.

Personal risk appetite

It doesn't make sense to take more risk than you are comfortable with. Taking on too much risk can lead to suboptimal behaviour, such as closing positions too early because you can't take the pain of the losses you have suffered. This is especially true if you are managing money for other people; you should only take risk that your clients can stomach. Institutional traders whose risk levels are too high will probably suffer heavy withdrawals by clients when their funds go into deficit territory.

In practice it's quite difficult to calibrate someone's risk appetite,[46] and even harder to do so in the somewhat abstract units of annualised percentage standard deviation. Of course, we could infer what a given risk target implies for the chance of a given daily or annual loss, but that requires making some unrealistic assumptions about the distribution of returns.

One possible solution is to present a selection of typical portfolios, and see which one best represents the trader or institutional client's appetite for risk. For example:

- For a diversified portfolio of bonds the annualised standard deviation will usually be between 2% and 8%, depending on the maturity and credit rating.
- A typical investment portfolio with a mixture of stocks and bonds will have risk of around 12%.
- A diversified portfolio of global stocks will probably have an annualised standard deviation of 15% a year.
- Blue chip individual stocks in developed markets typically have volatility of 20% to 40%.
- An especially volatile individual stock or a cryptocurrency could easily have an annualised standard deviation of over 100%.

Optimal risk given expected performance

Futures traders tend to have a higher tolerance for risk than most people, and the leverage on offer is very generous. So if you are comfortable with the possibility of large losses in a severe market crash, then risk targets of over 50% are not unachievable.

It feels like it would be highly imprudent to trade with that risk target, but would it also be unprofitable? Figure 11 shows the expected final account value for a long-only investor in the S&P 500 future, running with various risk targets. The figure assumes we begin with capital of one unit, and shows the final capital valuation at the end of a 40 year back test using compounded returns.

Figure 11: FINAL ACCOUNT VALUE given risk target for S&P 500 buy and hold strategy

It's clear from this plot that increasing the risk target gradually increases the final account value return we expect, until the target reaches around 40% a year. Thereafter the final account value falls sharply, and goes to zero once the risk target approaches 60% a year.

What is happening here? As our leverage and risk increases, our worst days are getting larger in magnitude. It then takes us longer to recover from those especially bad days. For modest increases in risk target this isn't a problem, since we get a larger offsetting benefit from improving our good days. But once our risk gets too high, those bad days really hurt.

Why do we end up losing all our money once the risk target is too high? Well, the worst day for this buy and hold S&P 500 strategy is a loss of 27% (in October 1987). The volatility of the S&P 500 is around 16%, so a risk target of 60% corresponds to a leverage factor of 3.75. If we leverage a 27% loss 3.75 times, then we'll lose over 100%. Of course, it's impossible to come back from a 100% loss.

The optimal level for our risk target is known as the **Kelly optimal risk**. From the graph above the Kelly optimal for this strategy is a risk target of around 38%. It can be shown that this level is theoretically equal to the SR for the underlying strategy, if the returns are Gaussian normal.[47] In this case the SR is 0.47,[48] which would normally equate to a Kelly optimum risk target[49] of 47%. The actual optimum is lower on this occasion, because S&P 500 returns are certainly not Gaussian normal. Assets with negative skew and fat tails require Kelly optimal risk targets that are lower than implied by their SRs.

Because returns are rarely Gaussian, and because Sharpe ratios are difficult to forecast, it's generally accepted that a more conservative risk target of **half Kelly** should be used. In this case we'd use half the full Kelly value of 47%, for a risk target of 23.5%.

In summary: to calculate the optimal risk target given an expected SR, we halve the expected SR and use the resulting figure as an annualised percentage standard deviation risk target. This will usually give a more conservative value for target risk than the other calculations in this section.

Summary: Target risk

To summarise then our target risk, measured as an annualised percentage standard deviation, should be the lowest value of the following:

- Risk possible given margin levels. This is set by the exchange, and/or the broker. As an example, for the S&P 500 micro future the maximum risk is around **313%**.
- Risk possible given potentially large losses. This depends on your ability to cope with extreme losses, e.g. for S&P 500, assuming we wish to survive a 1987-size crash with half our capital intact: **27%**.

- Personal risk appetite. This is determined by your own feelings, or those of your clients if you are trading external funds. This varies according to the trader, but is most likely to be in the range **10% to 100%**, typically with lower values for institutional traders.
- Optimal risk given expected performance. This depends on the return profile of your trading strategy. For S&P 500 using the backtested value for strategy one this is around **23%**.

The most conservative of these values is the final one: **23%**, derived from the half Kelly calculation assuming a SR of 0.46 (which is probably optimistic, but I'll let that slide for now). For simplicity I'm going to use a relatively conservative risk target of **20%** for the rest of this book, which is roughly in line with the target used by many institutional futures traders.

Risk scaling the S&P 500 micro future

Let's see how the buy and hold risk targeted strategy works in practice. We'll use the risk target of 20% per year we derived above, and an arbitrary capital of $100,000. Assuming the standard deviation of the S&P 500 is 16%, we get:

We'd have to recalculate the required optimal position every day, according to the current futures price and FX rate,[50] by taking the rounded value of *N*. Every time *N* changed we would have to buy or sell to ensure our current position was in line with what is required to hit our target risk. This would result in a number of trades, so this strategy will have higher trading costs than strategy one, where we only have to pay for rolling from one contract to the next. I'll discuss in more detail how I calculate trading costs in strategy three, but for now it's worth noting that these extra costs only reduce our returns for the S&P 500 by 0.17% a year.

In the backtest I don't use $\sigma_{\%}$ = 16%, but instead measure the average standard deviation over the entire time period[51] for which we have data. This comes in a fraction higher at 16.1%.

Discrete versus continuous trading

As you are no doubt realising, I trade futures a little differently to most people. The way I trade is common amongst quantitative hedge funds, but almost unknown for retail traders. You won't see any discussion in this book about 'opening a position', 'entry filters', 'closing out', or 'stop losses'. Those are all the hallmarks of *discrete* trading. I prefer to trade *continuously*.

What exactly do I mean by discrete trading? It's how most people trade. You decide to open a position. You buy a few contracts. Then at some point in the future you decide to close it. You can point to the chart and say, "This is where I opened my trade," and then point to another point and say, "Here is where I closed my trade." You can calculate your profits (or losses) on each individual trade. You will have an interesting story you can tell about every trade, which is nice, especially if you want to become one of those YouTube or Instagram trading gurus.

I don't get to tell interesting stories (as is becoming clear as you read this book!), because that is not what I do. Instead I *continuously* calculate an **optimal position** (although in practice for most of this book, continuously means once a day). That's the position I would like to have on right now. I then round it, since we can't hold fractional positions. Then I look and see what position I actually have on. If the two are different, then I trade so that my optimal and actual positions are equal.

This means I don't have discrete 'trades', in the sense of positions that were opened and then closed. If I turn on a strategy and it wants to be long three contracts, then I will immediately buy three contracts. If the next day it only wants to be long two contracts, then I will sell one. Maybe I will buy it back the next day. Depending on the strategy I am running, I will probably close the position at some point, and then go short. Where are the discrete trades? There aren't any. Just a series of buys and sells to ensure I always have the optimal position.

Of course, you can still use many of the strategies in this book as a discrete trader, and I will explain how later in the book. But, as I demonstrated in my previous book *Leveraged Trading*, continuous trading is more profitable and, as I will explain later in this book, makes it easier to trade multiple strategies.

Figure 12 shows the number of contracts held over time in the backtest for S&P 500 micro futures. We begin with nearly 250 contracts, since the initial price is just over $100, but by the end of the testing period we have just under six (as the price is over $4,000).

Figure 12: Position in contracts over time given risk scaling of S&P 500

Let us now turn to performance. We can use the same formula outlined back on page 24 to calculate the profit and loss in dollar terms, but with two important differences. Firstly, we have a varying number of contracts over time rather than just a single contract position. Secondly, when working out percentage returns we'll now use the fixed notional capital figure of $100,000 rather than the varying capital figure from strategy one.

One consequence of using fixed capital is that we don't need to plot cumulated account curves in both currency and percentage terms, since the graphs will be identical except for the *y*-axis. Personally I prefer to plot account curves in percentage terms, since the capital used is to an extent an arbitrary figure.

With that in mind, figures 13 and 14 show the daily percentage returns, and the cumulative sum of percentage returns respectively.

Figure 13: Daily percentage returns for S&P 500 buy and hold with fixed risk target

Figure 14: Account curve for S&P 500 buy and hold with fixed risk target

Compounding

Compounding of returns is a very important concept in finance, even if it's probably not "The strongest force in the universe," as Albert Einstein allegedly once said. Earning 10% a year for ten years will double your money with simple interest, but with compounding you can double your money in just over seven years and end up with 160% of your initial investment after ten.

However, with the futures trading strategies which I describe in this book, **we don't compound our returns when backtesting**. After a year of trading the S&P 500 with $100,000 where we've made a hypothetical 10%, we don't increase our capital to $110,000: instead it remains at $100,000. If we did compound, then we'd end up buying more contracts, and then making a greater dollar profit in any subsequent years. Since the number of contracts we hold isn't affected by any profits that we've made to date, we don't compound our returns.

(Strategy one is an exception to this rule. Because it uses the current price to decide how much capital to hold, it implicitly compounds its returns.)

I do this because cumulated account curves for compounded returns are hard to interpret. Assuming you have a profitable strategy, they will show exponential growth, with small variations early on, getting larger and larger over time. For example, figure 4 shows a compounded account curve for strategy one. You can barely see the crash of 1987 without a magnifying glass.

Instead, so that it's easier to see what's happening for the early years of a strategy, I cumulate percentage returns by summing them up over time (I use percentage returns as they can be easily compared, without considering the actual amount of capital traded). In my cumulated percentage plots 100 is equal to 100%, hence if you wanted to know how much profit you would have made trading a particular strategy with a given amount of fixed capital, you can infer this from the cumulated percentage plots.

From this point onwards, all the strategies in this book will show performance statistics and graphs for *non-compounded percentage returns*. Incidentally, this is why I was able to take an arithmetic mean of daily percentage returns when measuring the performance of strategy one, something that would be inappropriate for compounded returns (with compounded returns, to get an average we should really use the compound annual growth rate, CAGR, which is the annualised geometric mean of daily returns).

VERY IMPORTANT WARNING: it would be extremely dangerous to actually run your strategy with real money and fixed capital! An important consequence of Kelly (or half Kelly) risk targeting is that you should reduce your position size when you lose money. A simple way to achieve this is to **use the current value of your trading account as the notional capital** when calculating your required position. Then any losses you make will result in your positions being automatically reduced, and vice versa for profits.

How often should you update the figure for the value of your account that is used for position calculation? I update it daily, but then my system is fully automated. With a risk target of 20%, it's probably safe enough to update it weekly except when the market is under stress, in which case more frequent updates would be prudent. Institutional traders will have to consider the liquidity and rules of their fund, and will usually update their notional AUM on a weekly or monthly basis.

In the final part of this book I'll discuss in more detail other methods you can use to manage the compounding of your account.

Let's look at some performance characteristics:

Strategy: Buy and hold, single contract	S&P 500 micro future
Years of data	41
Mean annual return	12.1%
Average drawdown	−16.9%
Annualised standard deviation	25.0%
Annualised Sharpe ratio	0.48
Skew	−0.47
Left tail	2.21
Right tail	1.79

Overall these figures are better than for strategy one, although it's quite difficult to compare given the very different way that they handle capital. More interestingly, the annualised standard deviation comes in at 25.0%. This is pretty good, although it has overshot our target of 20% because of a few extreme days (if I used monthly rather than daily returns, I get a better annualised figure: 19.8%). Of course, we know from figure 13 that the risk is actually sometimes a lot higher, and sometimes a lot lower, than 20%. I'll address this problem in strategy three.

Minimum capital

In the example above I used $100,000 for the notional capital. But not everyone has $100,000 spare. What if you only had $5,000? How many micro contracts would you buy now, given the current S&P 500 price of 4500?

Futures contracts have one substantial disadvantage – they are indivisible. You can't buy or sell[52] 0.278 of a futures contract. This means we can't actually trade the S&P 500 micro future if we only had $5,000. What then is the minimum amount of capital that we need to trade the S&P 500 micro future? Let's rearrange the standard formula for position sizing:

The smallest number of contracts we can hold, N, is one, which implies:

For example, with the S&P micro future we get the following minimum capital with the current price of 4500, an estimated standard deviation of 16% a year, and a risk target of 20% per year:

That makes intuitive sense, as in figure 12 we have just over five contracts at the end of the data, using capital of $100,000.

However even $18,000 isn't likely to be enough. Suppose we started trading the S&P micro future with $18,000. On day one of trading we have a single contract. Then a couple of years later the price of the future has doubled (a nice problem to have!). Now the optimal number of contracts to hold is just 0.5. But we can't hold half a contract. We have the choice of either closing our position completely, in which case our expected risk will drop to 0%, or continuing to hold on to our single contract implying our expected risk will be twice its target: 40%.[53]

Neither option is ideal. To avoid this dilemma, it would be nice if we could start off with more than one contract. That way we'll have the option to adjust our position as prices and risk change (and as the FX rate changes, where relevant). As a rule of thumb I advise setting your minimum capital **so that you own at least four contracts when you begin trading**. Four contracts gives us enough wiggle room to keep our position risk at approximately the right level.

How much capital do we need if we want to own at least four contracts?

That would give us $72,000 for the S&P 500 micro future. Expressing the formula in terms of notional exposure per contract:

Note that minimum capital will be higher if:

- The futures multiplier is higher. Thus, if you have limited capital, it makes sense to use mini and micro futures if they are available: the full-size contracts will have higher minimum capital.
- The price and/or the exchange rate is higher. We would have required less capital in the past, when the S&P 500 future was much cheaper.
- Taken together, the above two points imply that minimum capital will be higher if *notional exposure per contract* is larger.
- Minimum capital will also be larger if the standard deviation of the instrument is higher. With limited capital you will find it difficult to trade especially risky instruments.

- You will require a higher minimum capital when your risk target is lower. This is potentially dangerous, since an apparently easy way to make the most of limited capital is to take more risk with it. Do not be tempted to do this!

Rather than murder several trees with a list of minimum capital for every instrument in my data set, I've put the relevant statistics on the website for this book. Still, it is interesting to look at some of the highlights, shown in table 5.

Table 5: Very large and very small minimum capital requirements

	Minimum capital		Minimum capital
Schatz (Bond)	$7,600	Palladium (Metal)	$1,880,000
US 2-year (Bond)	$15,600	S&P 400 (Equity)	$860,000
BTP 3-year (Bond)	$19,600	Gas – Last (Energy)	$844,000
Korean 3-year (Bond)	$24,400	US 30-year (Bond)	$552,000
VSTOXX (Volatility)	$26,400	Copper (Metal)	$548,000
Eurodollar (Interest rate)	$29,200	AEX (Equity)	$533,000
MXPUSD (FX rate)	$34,000	NOKUSD (FX rate)	$520,000
US 3-year (Bond)	$40,000	Gasoline (Energy)	$468,000

Current capital required to hold a single contract using a 20% annualised risk target.

Most of the smallest minimum capital instruments are bonds with short duration: the 2-year German (Schatz) and US bonds, and the 3-year Italian (BTP), Korean, and US bonds; plus the Eurodollar short-term interest rate futures. Bonds usually have lower volatility than other assets, with short duration bonds the safest of all.

The European volatility index (VSTOXX), and the MXPUSD FX future are also in this group. VSTOXX has a very low price – it was around 22.9 when I did this calculation (implying the expected standard deviation of the European Eurostoxx 50 index was 22.9% a year). It also has a low multiplier of just 100, in contrast to the US VIX which is also priced in volatility units but has a multiplier of 1000, and hence a minimum capital almost ten times larger ($250,000).

Similarly, the notional exposure per contract for MXPUSD is just $24,000; so even though it's relatively risky for a currency (standard deviation of 8.3% a year), the minimum capital is relatively modest.

At the other end of the spectrum, Palladium has a price of nearly $1,900 a contract, which combined with a multiplier of 100 gives it a notional exposure per contract of $189,500. But it's also insanely risky, with an annualised standard deviation of nearly 50%, resulting in a near two million dollar minimum capital requirement to hold four contracts.

How well does risk targeting work over different instruments?

Tables 6 and 7 show the average performance across different asset classes for strategy two. They are directly comparable with tables 3 and 4.

Table 6: Performance for fixed risk targeting across financial asset classes

	Equity	Vol	FX	Bond
Mean annual return	11.5%	−8.3%	1.5%	12.3%
Average drawdown	−8.7%	−76.9%	−29.2%	−12.5%
Annualised standard deviation	22.2%	21.8%	21.2%	21.4%
Sharpe ratio	0.48	−0.39	0.07	0.60
Skew	−0.40	2.27	−0.24	0.15
Lower tail	1.98	1.30	1.74	1.81
Upper tail	1.54	2.68	1.65	1.53

Table 7: Performance for fixed risk targeting across commodity asset classes

	Metals	Energy	Ags	Median
Mean annual return	6.7%	6.5%	4.5%	6.3%
Average drawdown	−38.3%	−33.4%	−45.5%	−15.0%
Annualised standard deviation	21.9%	22.5%	21.4%	21.5%
Sharpe ratio	0.31	0.29	0.20	0.34
Skew	−0.13	−0.20	0.45	−0.17
Lower tail	1.80	1.65	1.64	1.82
Upper tail	1.64	1.58	1.71	1.62

The relative picture is similar to strategy one. Equities have unpleasant skew and ugly tails but a decent SR. Bonds are better behaved, and have the highest SR of all. Volatility still has a negative SR, compensated for by positive skew and a fat right tail. The other assets sit somewhere between these extremes. Finally, as we would hope given we are explicitly targeting it, the standard deviation averaged across each asset class[54] isn't far off the target of 20%.

It is interesting to compare strategies one and two. The SR is better in strategy two for every asset class, with the median instrument improving from 0.13 to 0.34. That is nearly a threefold increase! Skew is also more positive across the board, with the negative skew of −0.38 for strategy one more than halved. These are spectacular improvements.

Conclusion

For strategy two I introduced the idea that we should calculate position size according to available capital, and we also saw that position sizing using a risk target resulted in a substantial improvement in performance compared to strategy one. Many people say that diversification is the only free lunch in finance. I would add that **risk targeting is the second free lunch** (or perhaps as I'm English, the free afternoon tea).

Although this strategy is more logical than the single contract version of strategy one, it is clearly still flawed. Even for instruments which do a better job of hitting the 20% risk target, such as the S&P 500, there is still substantially different risk over time. Skew and fat tails remain an issue. Strategy two is far from perfect: we can do better.

Strategy two: Trading plan

43 If we spend 68% of our time in the range, we must be outside of the range 32% of the time. Half of that time we will be above the range, and half the time (16%) below it. So 16% of the time we'll lose at least $2,500.

44 Notice that the standard deviation is unaffected by the volatility of the FX rate.

45 As happened in Crude Oil in the early part of 2020.

46 Many wealth management firms and financial advisers have developed questionnaires that try to quantify risk appetite, but this sort of exercise is a long way from being a precise scientific measurement.

47 This can be derived from the more commonly known optimum Kelly leverage, which is $f = \mu \div \sigma^2$ where μ is the average excess return, and σ is the standard deviation of the unleveraged portfolio. The optimal target risk with this leverage factor is $f\sigma = \mu \div \sigma$, which is equal to the SR. The Kelly optimum, or Kelly criterion, was developed by John L. Kelly at Bell Labs in 1956 and popularised by Ed Thorp, who started as a card counter before becoming one of the most successful hedge fund managers in history. See the bibliography in Appendix A.

48 There is an apparent chicken and egg problem here. To calculate the optimal risk target you need the expected SR, for which you probably need to run a backtest, which requires knowing what risk target to use! In practice, since the SR is a risk adjusted measure, you can just run an initial backtest at some nominal risk target, then calculate the SR, and then decide what your final risk target should be. Finally, run a backtest with the appropriate risk target to understand the system's likely behaviour. Or don't run a backtest, and just use the recommended risk target of 20% a year.

49 In practice I'd probably be quite sceptical about expecting an SR of 0.47 for a buy and hold strategy on the S&P 500 for reasons I'll explain later, but at this stage it's more important to understand the calculations.

50 For now we don't recalculate our estimate of $\sigma_{\%}$; I will do this in strategy three.

51 Strictly speaking, this is a forward looking in-sample estimate and hence cheating, since we wouldn't have known that figure when we started our hypothetical trading in the early 1980s. I'll address this point in the next chapter.

52 Some brokers offer other products such as spread bets and contracts for difference which are sized so they are fractions of a futures contract, but these are not actually futures. See *Leveraged Trading* for more information.

53 We would have the same problem if the risk ($\sigma\%$) halved. It's also possible, but probably unlikely, that the FX rate could halve.

54 Rebalancing purely because of price changes – as we do in strategy two – could mean we are affected by a phenomenon known as the *leverage effect* in equity futures. In this theoretical setup firms which hold debt will get riskier when prices fall, so we end up with more risk from buying more stock. Hence we'd expect higher risk, and poorer risk targeting, for equities. In practice I don't find significantly different results here across different asset classes.