



## MODULE 3 UNIT 3

# IDE Activity Video 1 Transcript

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STEFAN ZOHREN: Hi, everyone. In the following, I want to give a very short tutorial about momentum strategy. So that's a tutorial which we put together with some colleagues at the Oxford-Man Institute. And we'll give you some basic idea of how the systematic strategies work.

So, we start off with looking at a long-only strategy for a financial instrument. Then we see the benefits of volatility targeting and how that helps to reduce the risk. Then we introduce some other strategies, such as simple time series momentum, as well as MACD strategies. And we will see how combining different strategies leads to better risk-adjusted performance.

Let's just run a little bit through the details of the tutorial. So, at the beginning we have also a few links if you want to read some more references. The paper by Harvey talks a little bit more about volatility targeting. Then we have the two papers by Moskowitz and Baz, which describe the main strategies on time series momentum. And we also have a link of one of our papers, which discusses some machine-learning extensions of such works.

So, let's just get started with the code here. So first, after some basic imports to get the relevant libraries, we load the data. As I mentioned in the introduction, so, we just look at one instrument here. In our case, we look at the S&P 500 time series. Now, in reality, first of all, you would have to find a kind of instrument, like a spiral future to trade, actually, the S&P 500. And you would obviously, probably, look at more instruments as well.

But for simplicity, we just look at one instrument here and we just load the data first for the S&P 500 time series. We have the open, high, low, close here, as well as volume. And then we just focus in and we look at the data from 1990 to the end of 2009. So that's the data we will be looking at. You're invited to also have a look at other instruments, as well as other time periods. But as I said, really, you need a lot of instruments to get very good statistics. So, in this case, we have just one as an example. And this period actually looks very, kind of, representative of how such a strategy would actually look on average for more instruments.

So, we start off very simply by just plotting the close price. And we see here, the evolution of the S&P 500 over this, kind of, 20-year range from 1990 to the end of 2009.

Now, the first exercise you were asked to do was a simple warmup exercise to calculate the returns here. And you were asked to fill in the code. So, here you can see the solution.

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```
In [5]: data = data_hist["1988-12-01":"2009-12-31"].copy()
```

After correctly loading the price series data and adding the one year buffer, you will next calculate the returns from time  $t - \tau$  to  $t$ , using the following formula,

$$r_{t-\tau,t} = \frac{p_t - p_{t-\tau}}{p_{t-\tau}},$$

where  $p_t$  is price at time  $t$  and  $\tau$  is the offset, the number of days we calculate the returns over.

**Exercise:** Complete the following function.

```
In [ ]: def calc_returns(srs, offset=1):
    """
    Parameters:
        srs: pandas time-series
        offset: number of days to offset returns
    Returns:
        Calculates the returns over the past number of days
        specified by offset
    """
    ### Enter code here
    returns = srs / srs.shift(offset) - 1.0
    ###
    return returns
```

Next, you want to print the return of the previous day as well as the following day's return, which you will use to evaluate the strategy.

```
In [ ]: data["daily_returns"] = calc_returns(data["Close"])
data["next_day_returns"] = data["daily_returns"].shift(-1)
data.head(1)
```

It's actually quite simple. We just use the price series and we take the price series divided by the price series shifted by the offset, which is the previous day or previous more than one day, if the offset is a number larger than 1. And then we just subtract 1, which follows from the formula above.

The first exercise was hopefully pretty straightforward. We can now augment our data frame by adding the daily return. And we can also add the next-day returns as well, as it's done here in the following.

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```
    """
    Parameters:
        srs: pandas time-series
        offset: number of days to offset returns
    """
    ### Enter code here
    returns = srs / srs.shift(offset) - 1.0
    ###
    return returns
```

Next, you want to print the return of the previous day as well as the following day's return, which you will use to evaluate the strategy.

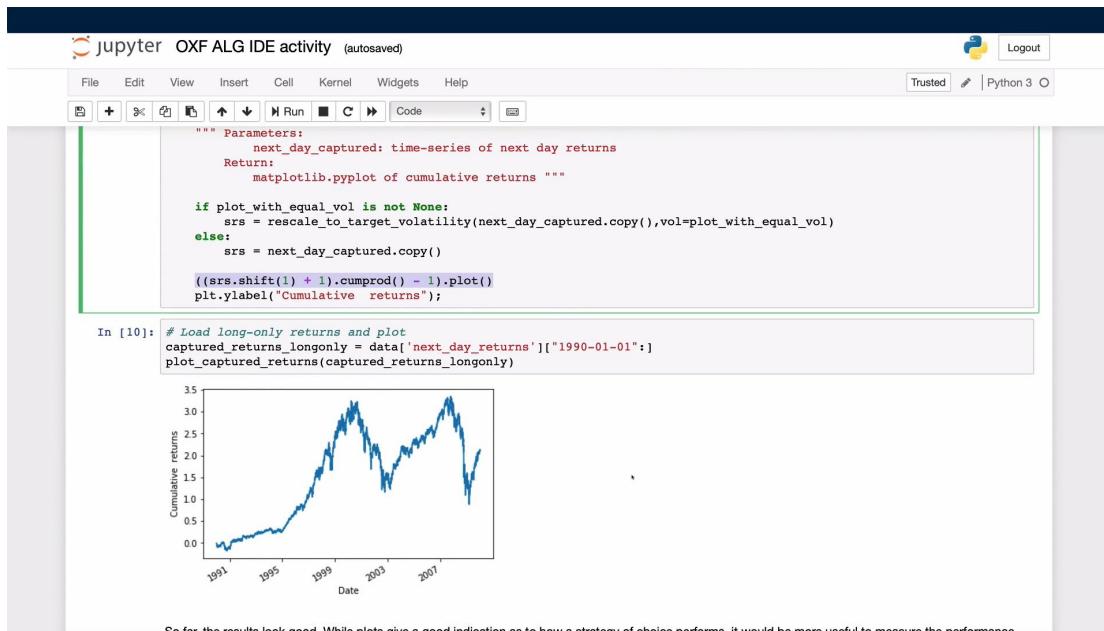
```
In [7]: data["daily_returns"] = calc_returns(data["Close"])
data["next_day_returns"] = data["daily_returns"].shift(-1)
data.head(1)
```

Date	Open	High	Low	Close	Volume	Dividends	Stock Splits	daily_returns	next_day_returns
1988-12-01	273.679993	273.700012	272.269989	272.489990	129380000	0	0	NaN	-0.002495
1988-12-02	272.489990	272.489990	270.470001	271.809998	124610000	0	0	-0.002495	0.011479
1988-12-05	274.929993	275.619998	271.809998	274.929993	144660000	0	0	0.011479	0.009675
1988-12-06	274.929993	277.890015	274.619995	277.589996	158340000	0	0	0.009675	0.001945
1988-12-07	277.589996	279.010010	277.339996	278.130005	148360000	0	0	0.001945	-0.005537

It is sometimes advisable to [winsorise](#) the data by capping or flooring it to be within 5 times its exponentially weighted moving (EWM) standard deviations from its EWM average. In this way, you can mitigate the effects of outliers when calculating the trend. You can winsorise the data and then plot the daily returns using the following lines of code.

Now, the next bit is about winsorising. So, winsorising is just a way of, a little bit, removing some outliers from the data. So, what we do here is, we look at a threshold of five standard deviations calculated over a year, and we basically clip any returns which go above that. So, this basically removes outliers. And it can be helpful in training strategies, especially if you do machine learning-type of strategies, which we don't do here, but as we mentioned earlier, there are some follow-up works, like the paper mentioned above, which discusses some machine-learning extensions. And that can be very useful, at least on the training data, to do such transformations there.

So, let's just look at the main strategies. So, the first strategy we look at is long-only. So, long-only, which is kind of buy and hold, which is very easy. And we can look at the long-only strategy and we just plot the returns. To do so, we calculate the cumulative returns. For that, we just take the return series, we add 1. So, for example, if we had 6% return, we now had 1.06. And then we multiply all those returns and at the end subtract 1. So, this is how we get the cumulative returns. And you can see a plot of those returns here at the bottom, which is the entire return series over those 20 years.



Now to evaluate this – the performance of this strategy – we need some performance metrics here. So here we have some basic performance metrics. So, something where most of you are interested are, obviously, returns, which is just the expected value of the daily returns times the number of days which we're looking at. In this case, we have a year, which is 252 business days.

Then we have volatility. And again, it is important to, kind of, normalize volatility to be annual. So, the square root of the variance of the returns will just be the daily volatility. And we have to analyse that to get the correct numbers.

Then we have downside deviation and maximum drawdown. And here we implement all those measures. We first implement the downside deviation, maximum drawdown. So, those formulas were given to you.

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And now in the following, we want to evaluate the risk-adjusted performance metrics, where we have the Sharpe ratio, which is just expected returns over the standard deviation of the returns. Again, annualised to a whole year.

Then we have the Sortino ratio, because the issue with Sharpe ratio is that it kind of treats volatility, or variations of surprise, whether they go up or down, equal. But obviously, in reality, if the price swings upwards, we don't really mind. But if it swings downwards, we want more. So, in this case, we calculate the Sortino ratio, which kind of penalises the upward moves and just focuses on the downward moves there.

Similarly, the Calmar ratio is the kind of analog definition, where we replace the volatility from the Sharpe ratio with the maximum drawdown. So those are the three metrics we look at.

In the following, we implement those metrics here. Given that we already calculated volatility, downside deviation, and max drawdown, it was very simple to just fill in those formulas.

The only important thing was to keep track of the correct normalisations here. So, square of 252 years for the Sharpe ratio, which gives us the correct annual normalisation. And similarly for Sortino. For Calmar, it's slightly different. It's just multiplied by 252.

So those are the correct normalisations. And now we have the function, which plot all the performance matrixes. So here in this case, we see the actual long-only strategies has just 7.39% annualised performance. But it has very high volatility. See, 18.6% volatility.

Downside deviation is also high and maximum drawdown 20%. That's not so good. And you can see, for example, Sharpe ratio is only 0.4.

SPEAKER: If you would like to review any of these sections, please click on the relevant button.