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The profitability of CFD day trading on the JSE

1. INTRODUCTION

Trading in the warrant, CFD ("contract for difference"), SSF ("single stock future") and other derivative markets is popular because it provides the trader gearing to stock price movements, thus enabling trades with potentially larger returns both when prices increase and when they decrease. However, such trading is also more risky implying that the trader can lose money faster with this form of trading than with conventional trading if price movements are not anticipated correctly often enough. A trader's skill can be measured by the probability that the trader anticipates the price movements correctly. A highly skilled trader will enter enough profitable trades to make up for the occasional losses while a low skilled trader will lose more than can be made up for by the occasional profits. What are high and low skill levels in this context and how do they depend on trading costs and market features such as trends and volatilities? This paper reports the results of studies on these issues specifically for the case of CFD day trading in the large cap stocks of the JSE.

Two findings stand out. Firstly, the success of CFD day trading is highly dependent on the brokerage rate and secondly, relatively high skill levels are required for success, especially when the brokerage rate is high. A typical result shows that over the last 40 months the CFD day trader in Anglo American who pays 0,5% brokerage rate needed to anticipate price movements correctly with about 77% probability if he wished to be sure of success. If his brokerage rate was lowered to 0,25% then only 69% probability of correct anticipation was required for success. Another finding is that trading in more volatile shares has substantially better chance of success at lower skill levels. Thus CFD day trading in the more volatile share Angloplat required only about 61% probability of correct anticipation at brokerage rate 0,25%. The CFD trader in these results makes one of three possible decisions every day, namely the price will move up, down or sideways and trades accordingly. We also study the case of a trader who distinguishes only between up and down movements and find that such a trader requires even higher skill levels for success.

The results reported here are related to the literature on **market timing**, starting with the paper of Sharpe (1975) and followed by many others such as Chua, Woodward and To (1987), Droms (1989), Kester (1990a, 1990b, 1992) and Wong and Tai (2000). The studies reported in these papers were based on data from stock exchanges in the US, Canada, Japan, Hong Kong and Singapore. They dealt with longer term trading in which portfolio rebalancing was done on a monthly, quarterly or yearly basis. Switching was allowed mainly between stocks (long only and in the form of market indices) or a risk free money market account. A sample result from Sharpe (1975:66,67) states that " ... a manager who attempts to time the market must be right roughly three times out of four.. ". This 75% skill level is quite in line with the results of our study related to CFD trading on the JSE. It appears that the earlier conclusions are largely also valid for very high frequency trading in which long and short portfolios as well as gearing via CFD's are allowed and the criteria for judging success are rather different.

Section 4 of this paper provides the details of the simulation studies on which our findings are based and sets out more fully the assumptions and arguments that need to be kept in mind when interpreting them. Section 2 prepares the way by developing formulas that express the return on CFD trades in terms of the returns on the underlying shares and the brokerage rates and Section 3 provides more details on measuring trading skills in terms of the probability of correct anticipation. Section 5 concludes with an overview of the research findings and suggested areas for future research.

2. CFD RETURN FORMULAS

Broadly speaking a CFD trade differs from a conventional trade in that only a fraction (the "margin") of the full value of the trade needs to be paid at the time of entering while the full outcome of the subsequent price movements accrues to the trader. This is the cause of the gearing effect. More detailed explanations on CFD's can be found in many sources; searching Google with "CFD trading" produces more than a million items. Here we largely follow a local CFD trading provider, PSG Online (https://www.psg-online.co.za). To better understand CFD trades we now develop formulas relating the return on such trades to the return on the underlying stock over the duration of the CFD contract. Henceforth we restrict attention to **day trading**, i.e. the trader enters and exits the CFD contract within one day so that interest and dividends are not involved.

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We consider a **long** CFD and introduce the following notation:

- p_0 is the price of the stock at the time of entering the trade;
- p_1 is the price of the stock at termination;
- $r = (p_1/p_0) - 1$ is the return on the stock price movement;
- c is the brokerage rate;
- m is the CFD margin.

If n shares are involved in the trade, the initial contract value is np_0, the trader pays the margin and brokerage on this value amounting to $mnp_0 + cnp_0 = (m+c)np_0$ while also borrowing the rest of the contract value amounting to $(1-m)np_0$ from the broker. On termination the contract value is np_1 and brokerage on this is cnp_1; also the borrowed amount must be repaid. Thus the amount due to the trader on termination is $np_1 - cnp_1 - (1-m)np_0$. The trader's profit is

$$np_1 - cnp_1 - (1-m)np_0 - (m+c)np_0 = n[(1-c)p_1 - (1+c)p_0]$$

and expressing this relative to the initial investment we get the return on the trade, namely $R = n[(1-c)p_1 - (1+c)p_0]/(m+c)np_0$. Dividing through by np_0, we find that n drops out and if we also substitute $p_1/p_0 = 1+r$ the trade return simplifies to

$$R = \frac{(1-c)r - 2c}{m+c} \qquad \text{… (1)}$$

Since c is usually small compared to 1 and to m an approximation is obtained by replacing $1-c$ and $m+c$ by 1 and m respectively. The result is the simple expression

$$R \approx (1/m)(r - 2c) \qquad \text{… (2)}$$

which clearly demonstrates the gearing effect of the margin factor. For example, if $m = 20\% = 1/5$ then (2) becomes $R \approx 5(r - 2c)$ which says that the CFD return is about 5 times what we get by subtracting twice the brokerage rate (due to both a buy and a sell being involved) from the stock price return. While the gearing effect is clearer from (2) we used the more exact formula (1) in the simulation studies undertaken.

In the case of a **short** CFD contract, the initial outlay is again the margin and the brokerage on selling the share, amounting to $mnp_0 + cnp_0 = (m+c)np_0$. On termination the trader gets the initial contract value and his margin back, but has to pay the buy back cost of np_1 together with brokerage of cnp_1. Hence the profit is

$$np_0 + mnp_0 - np_1 - cnp_1 - (m+c)np_0 = n[(1-c)p_0 - (1+c)p_1].$$

Dividing by the initial outlay, we get the trade return. Again n drops out and if we also substitute $p_1/p_0 = 1+r$ the trade return becomes

$$R = \frac{-(1+c)r - 2c}{m+c} \qquad \text{… (3)}$$

which can be approximated by

$$R \approx (1/m)(-r - 2c) \qquad \text{… (4)}$$

when c is small. This differs from the long case formula (2) only in that r is replaced by $-r$ reflecting the fact that a short CFD can only yield a positive return when the stock price declines. Again the return is geared by the inverse of the margin factor as in the long CFD case.

3. MEASURING CFD TRADING SKILLS

To make a profit on a long CFD trade the share return r must be greater than $2c/(1-c)$ according to (1) and to make a profit on a short CFD trade the share return r must be less than $-2c/(1+c)$ according to (3), i.e. the share price must decline by at least the fraction $2c/(1+c)$. Let us define the event "up" by the outcome $r > 2c/(1-c)$, the event "down" by $r < -2c/(1+c)$ and "sideways" by the outcome that r is between these two limits. Before entering a contract the day trader has to decide which one of these three events will happen on that day for the share involved. If he decides on "up" he will enter a long CFD, if on "down" he will enter a short CFD and otherwise stay out. The trader's decision may rest on some formal prediction method or it may just be an informal judgment amounting to a subjective summary of available information or it may involve elements of both formal and informal analysis. Here we attempt to avoid dealing with the particular methodology used, focusing only on whether the net result is correct or not. The extent to which the trader's decision is correct expresses his skill and this can be measured by the probability that he makes the correct decision in the process.

In principle a trader can estimate his own skill without actually trading. To be more specific, suppose that the decision for the day must be made in the first hour of trading and that the trade must be terminated over the last hour of the day. Then the trader can record his decision over the first hour every morning and also note the actual return on the share at the termination time over the last hour for a test period of many days. From these records he can simply calculate the percentage of days on which he made the correct decision and this is an estimate of his skill level. Clearly, this may be different for different shares and it may also vary over time for the same share, possibly depending on market trends and events affecting the particular share.

We shall also consider a **directional** day trader who operates in terms of only two events, namely "up" if $r > 0$ and "down" if $r < 0$ (he tacitly assumes that r is never exactly 0). If this trader anticipates an up he enters a long CFD, if he anticipates a down he enters a short CFD and by implication he trades every day. To distinguish between the two types of traders we refer to the first one as an "up, down, sideways (UDS)" and to the second as an "up, down (UD)" trader. The UD-trader can also measure his skill by the probability of making the correct decision and estimate it in the same way as the UDS-trader described above. Supposing an UDS- or UD-trader conscientiously estimated his skill level, what does the result imply in terms of making money with CFD trading? This is the main question investigated in this paper. The details of the study are presented in the next section.

4. RESULTS OF CFD SIMULATION STUDIES

4.1 Empirical data

Some assumptions are needed to study the potential benefits of CFD day trading by simulation. We assume that if the day trader decides on "up" or "down" he enters the CFD at the volume weighted average price (VWAP) of the share over the first hour of trading (p_0) and terminates at the VWAP over the last hour (p_1). We have access to historical tick-by-tick data for all shares traded on the JSE over the last 40 months via the BMI-IDDB (the intra-day JSE price database maintained at the BMI Centre of North-West University). We selected the top 10 cap shares and calculated the historical daily values of p_0 and p_1 as well as the corresponding returns $r = p_1/p_0 - 1$ over the last 40 months ($T = 848$ trading days, retaining only full trading days). Table 1 gives some statistics on this data.

As is usual with intradaily returns, the averages are very small. The standard deviations are about 1,4% varying from 1,08% for the least volatile share (SAB) to 1,93% for the most volatile share (AMS). The skewness is also small suggesting that the returns are roughly symmetrically distributed but the (excess) kurtosis is positive suggesting that the distributions are not normal. The percentages of days with ups, downs and sideways movements were calculated at the brokerage rate of $c = 0{,}5\%$ and it is clear that ups and downs occur about equally often with frequency varying around 21%, SAB having the smallest and AMS the largest frequencies of ups and downs respectively. At the brokerage rate of $c = 0{,}25\%$ (not shown in this table) the splits between up, down and sideways are more evenly balanced being about 34%, 32% and 34% respectively, again with the ups and downs being more frequent than these numbers indicate for the more volatile shares and less for the less volatile shares. The lag one auto-correlations are all quite small suggesting that there is little time dependence between intra-daily returns over successive days.

4.2 CFD day trading oracles

If a UDS-trader with the ability to anticipate up, down or sideways days perfectly (an oracle) cannot make money with CFD day trading then anyone else with less than perfect skill will have even less scope for success and it would not make sense to investigate further. So the first issue to settle is: how well will an oracle do? Suppose the oracle starts with initial capital $C_0 = 1$ and trades over time in only one fixed share. If he (always correctly) anticipates an up on day t he invests all his capital in a long CFD so that his capital will grow to $C_t = C_{t-1}(1 + R_t)$ with C_{t-1} his capital at the end of the previous day and R_t the CFD trade return given by (1) with r replaced by the share return r_t for that day. Similarly, if he (again correctly) anticipates a down day he goes short and the growth in capital is calculated in the same way but using (3). On sideways days his capital stays fixed (we ignore the possibility of earning interest on such days). Given the record of returns over time the trader's terminal capital C_T is easily calculated. It is convenient to express the result in terms of the corresponding percentage annualised continuously compounded rate (ACCR). Assuming that there are 250 trading days in a year so that we have 848/250=3,392 years of data in our study, this number is given by $ACCR = 100\ln(C_T)/3{,}392$. Table 2 shows the ACCR values achieved by such an oracle (referred to as a UDS-oracle because of the UDS-trading considered here) for each one of the different shares and at different brokerage rates and with the CFD margin at $m = 20\% = 0{,}2$.

Table 1: Summary statistics of daily first to last hour VWAP returns

Share	Mean	StDev	Skewness	Kurtosis	%up	%down	%sideways	Autocorr
AGL	0,0002	0,0138	0,1894	1,1327	21,23%	22,41%	56,37%	-0,0478
BIL	0,0002	0,0133	0,1161	1,0540	19,58%	21,58%	58,84%	-0,0870
SAB	0,0003	0,0108	0,3002	1,9215	16,39%	15,21%	68,40%	-0,0326
RCH	0,0002	0,0126	0,1243	1,0421	20,17%	18,99%	60,85%	-0,0160
AMS	0,0008	0,0193	0,1306	0,4603	28,89%	27,71%	43,40%	-0,0884
MTN	0,0000	0,0169	0,0153	0,7084	24,41%	25,83%	49,76%	0,0636
SOL	0,0001	0,0153	-0,1057	1,1887	21,34%	22,41%	56,25%	0,0465
SBK	0,0005	0,0134	0,0136	1,0600	22,52%	18,87%	58,61%	-0,0071
OML	0,0012	0,0119	-0,0271	0,7222	19,93%	15,68%	64,39%	-0,0165
FSR	0,0002	0,0132	0,1758	1,4419	20,28%	20,40%	59,32%	0,0054
Average	0,0004	0,0140	0,0933	1,0732	21,47%	20,91%	57,62%	-0,0180

Table 2: %ACCR returns of an UDS oracle at varying brokerage rates and 20% margin

Share	c=0,00%	c=0,25%	c=0,50%	c=0,75%	c=1,00
AGL	1258	758	428	226	116
BIL	1213	712	398	213	110
SAB	985	504	242	105	43
RCH	1156	659	350	176	84
AMS	1749	1227	838	551	353
MTN	1529	1014	651	404	245
SOL	1363	863	534	322	186
SBK	1220	725	409	213	107
OML	1103	608	319	157	71
FSR	1209	705	383	199	99

Some of the returns are exceedingly large and cannot be realised in practice since they would imply that the oracle bought the entire company many times over. Still the implications are clear, namely that at brokerage rates below 1% an oracle CFD trader would have amassed a large amount of money over this period and that the amount rises dramatically at smaller brokerage rates. In Table 1 above it can be seen that AMS was the most volatile share in the sense that it had the largest return standard deviation and also the largest numbers of up and down days. In Table 2 this leads to AMS providing the oracle trader with the best capital growth opportunities even at high brokerage rates. Also SAB had the lowest volatility and this leads to it providing the least growth opportunities. Indeed the ACCR returns are almost linearly related to the share standard deviations as shown in Figure 1 which displays the column entries of Table 2 as functions of the share standard deviations of Table 1.

Of course an oracle with the ability to anticipate perfectly simultaneously the returns of all shares will be able to do even better than the one above who could only handle one particular share at a time. Such a higher oracle would select the share with the highest positive or lowest negative return on each day and take a long or short CFD in that share, thus maximising his capital growth on every day over all possible shares.

Rather than pursuing a higher oracle, consider next a somewhat lesser oracle, namely one who can perfectly anticipate the return direction of a share but not whether the return will be larger than the upper threshold $2c/(1-c)$ or lesser than the lower threshold $-2c/(1+c)$ also. This oracle is a perfect UD-trader and we refer to him as a UD-oracle. He always anticipates correctly a positive share return, taking a long CFD in this case, and also anticipates correctly negative returns, taking a short CFD in that case. Note that whereas the UDS-oracle never loses money the UD-oracle will lose if the share return is positive but less than $2c/(1-c)$ and also when the share return is negative but larger than $-2c/(1+c)$. If brokerage is zero they are identical, but otherwise the UD-oracle is in a poorer position than the UDS-oracle, reflecting his "lesser" status. Table 3 shows the ACCR returns achieved by the UD-oracle.

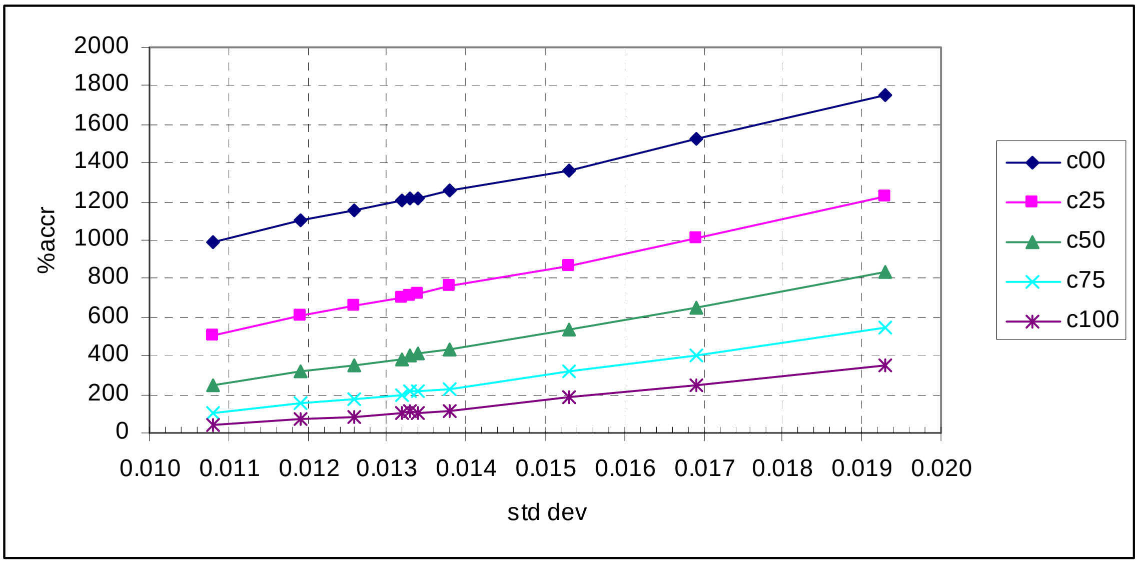

Figure 1: %ACCR of an UDS oracle as function of share volatility at various brokerage rates and 20% margin

Table 3: %ACCR returns of an UD-oracle at varying brokerage rates and 20% margin

Share	c=0,00%	c=0,25%	c=0,50%	c=0,75%	c=1,00%
AGL	1258	648	38	-571	-1181
BIL	1213	603	-8	-618	-1228
SAB	985	372	-241	-854	-1467
RCH	1156	545	-66	-677	-1288
AMS	1749	1144	540	-64	-667
MTN	1529	922	316	-291	-897
SOL	1363	755	146	-462	-1071
SBK	1220	610	-1	-611	-1221
OML	1103	491	-121	-733	-1345
FSR	1209	599	-11	-621	-1232

At zero brokerage there are no differences between the entries of Tables 2 and 3, but otherwise the UDS-oracle does better. If the brokerage is low the UD-oracle still does well but with increasing brokerage his performance quickly deteriorates. For example at 0,5% brokerage he has positive returns only on the more volatile shares and at 0,75% and higher he does not survive at all. Evidently, at higher brokerage rates the UD-oracle may have the direction of movement correct but the losses caused by high brokerage when the size of the movement is too small overwhelms the profits due to large size movements. It is clear that the extra ability of the UDS-oracle, namely to anticipate the critical size of the share return movements, is a large advantage when compared to the UD-oracle. Real traders are more likely to resemble the UD- rather than the UDS-oracle and to the extent that this is true, data in Table 3 suggest that real traders should not attempt CFD day trading if their brokerage rate is above 0,5%.

4.3 CFD trading with imperfect skill: UDS trading

Next we consider a UDS-trader with skill lower than that of a UDS-oracle, i.e. on each day, following some methodology, the trader chooses one of the three possibilities up, down or sideways and his probability of being correct is p which is less than 1 (or less than 100% when we express probabilities in terms of percentages). Here p expresses the skill level of the trader and we wish to vary it to establish its influence on the trader's performance. However, the simulation process is somewhat more complicated in this case and assumptions more explicit than just "being correct with probability p" are needed to make it work. We assume again that trading is done in only one share over the whole period. From a simulation point of view, on any given day we know the share return and hence also whether that day is really up, down or sideways. But the trader (or his methodology) does not know this and chooses the correct one only with probability p. To make this more precise, more notation is required. Let U, D or S denote the event that a day is actually up, down or sideways respectively and let CU, CD or CS denote the event that the trader chooses up, down or sideways respectively. Then we assume that the trader is equally good at choosing correctly up, down and sideways days, i.e. in terms of conditional probabilities we assume that $P(CU|U) = P(CD|D) = P(CS|S) = p$. By the law of total probabilities this guarantees that his unconditional probability of being correct is

$$\begin{aligned} P(\text{Correct}) &= P(\text{Correct}|U)P(U) + P(\text{Correct}|D)P(D) + P(\text{Correct}|S)P(S) \\ &= P(CU|U)P(U) + P(CD|D)P(D) + P(CS|S)P(S) \\ &= p[P(U) + P(D) + P(S)] \\ &= p \end{aligned} \quad \ldots (5)$$

as required. In these expressions $P(U)$, $P(D)$ and $P(S)$ refer to the probabilities of up, down and sideways days respectively and we assign to them the values of the relative frequencies of these cases as given in terms of percentages in Table 1. Since there are two possibilities to choose from in the event that the trader does not decide correctly and since his decision affects his actions, we need an assumption also on the probabilities of making these other choices. For example, given an up day, we need $P(CD|U)$ and $P(CS|U)$. Clearly, we must have $P(CD|U) + P(CS|U) = 1 - p$ but this is not enough to determine the two probabilities separately. Perhaps the simplest assumption is that if the wrong choice (either CD or CS) is made the split between these two will be in the same ratio as their relative frequencies of occurrence. This will imply that

$$\frac{P(CD|U)}{P(CS|U)} = \frac{P(D)}{P(S)} \quad \ldots (6)$$

Solving the two equations for $P(CD|U)$ and $P(CS|U)$ it then follows that

$$P(CD|U) = [1-p]\frac{P(D)}{P(D)+P(S)}$$

and … (7)

$$P(CS|U) = [1-p]\frac{P(S)}{P(D)+P(S)}$$

Hence in the simulation process, if a given day is an up day, we draw a uniform random number between 0 and 1 (say N) and if $N \le p$ we assign the trader the choice up (he correctly takes a long CFD), if $p < N \le p + P(CD|U)$ we assign down (he mistakenly takes a short CFD) and otherwise we assign sideways (he mistakenly stays out). Analogous expressions and implementations hold for down and sideways days in the simulation calculations. The relation $C_t = C_{t-1}(1+R_t)$ can again be used to update his capital with R_t determined by (1) or (3) if we assigned long or short and $R_t = 0$ otherwise.

The terminal capital and the equivalent ACCR return will now be random variables since they depend on the random numbers used for any particular simulation run. By doing many repeated runs we can estimate the probability distribution of the ACCR return. To illustrate, Figure 2 shows the estimates (based on 5000 simulation runs) of the probability densities of the distributions of the ACCR return when trading in AGL at skill levels of 70%, 75% and 80% respectively with brokerage at c=0,5% and margin at $m = 0,2$. We also show fitted normal densities based on the estimated means and standard deviations of the ACCR returns of the three cases. It is clear that these normal distributions provide reasonable descriptions of the actual distributions, although the latter seem slightly skewed to the left. At a skill level of 70% there is a large probability of about 92% of losing money (area under the density to the left of 0 is about 0,92). At a skill level of 75% the distribution shifts to the right and now the probability of losing money reduces to only about 20%. In fact there is now a probability of about 12% to more than double the capital annually (area under the density to right of $100\ln(2) = 69,31$ is equal to 0,12). At a skill level of 80% it is virtually certain that the return will be positive and in fact there is a probability of about 88% to more than double the capital annually; moreover an ACCR return of some 109% can be expected, corresponding to annual capital growth by the factor of $\exp(1,09) = 2,97$. Thus the skill levels below 70% are dangerous in the sense that they are highly likely to lead to disaster when CFD trading in AGL while skill levels higher than 80% are safe in the sense that they are highly likely to yield excellent performance. Between these levels varying degrees of success may be expected.

The notions of critically dangerous and safe skill levels can be tied to percentiles of the distribution of ACCR returns. Take a large probability (confidence level), say 95%, and compute the 95% and 100-95=5% percentiles of the distribution of returns as functions of the skill level. Figure 3 illustrates these for trading in AGL. The 95% percentile graph crosses the 0 return level at skill just below 70% so that at this or lower skill, there is at least 95% probability of a negative ACCR return. This makes the 70% skill level critical on the dangerous side. Analogously, the 5% percentile graph crosses the 0 return level at skill of about 77% so that at this or higher skill level there is at least 95% probability of having positive ACCR return, which makes the skill level of 77% critical on the safe side. Skill levels in the interval between 70% and 77% correspond to varying degrees of success in performance. We shall refer to these two skill levels as the critical skill levels (CSLs) at 95% confidence. The lower CSL (denoted by CSLL) measures the skill which is likely to lead to ruin and the higher CSL (denoted by CSLH) measures the minimum skill needed to ensure success, both with at least 95% probability.

Table 4 shows these 95% confidence CSL values for all shares and at different brokerage rates. At brokerage of 1% near oracle skills are required just to avoid ruin. Even at brokerage of 0,75% the required CSLL seems quite high for typical CFD traders. Accordingly, it is quite clear that low brokerage is of prime importance for success in CFD day trading. At low brokerage rate the CSLs are about the same for the different shares but with increasing brokerage the differences become substantial and the critical levels decrease with the volatilities of the shares as measured by their standard deviations. For the case c=0,5%, Figure 4 plots the CSLs of the various shares against the standard deviations as given in Table 1. Clearly, the more volatile the share, the lower the CSLs required, i.e. the easier it is to CFD day trade successfully in that share. This is to be expected since higher volatility implies larger positive or negative returns and the more frequent larger profits when the trader is correct will still outweigh the less frequent losses when the trader is wrong as long as his skill level is above 50%.

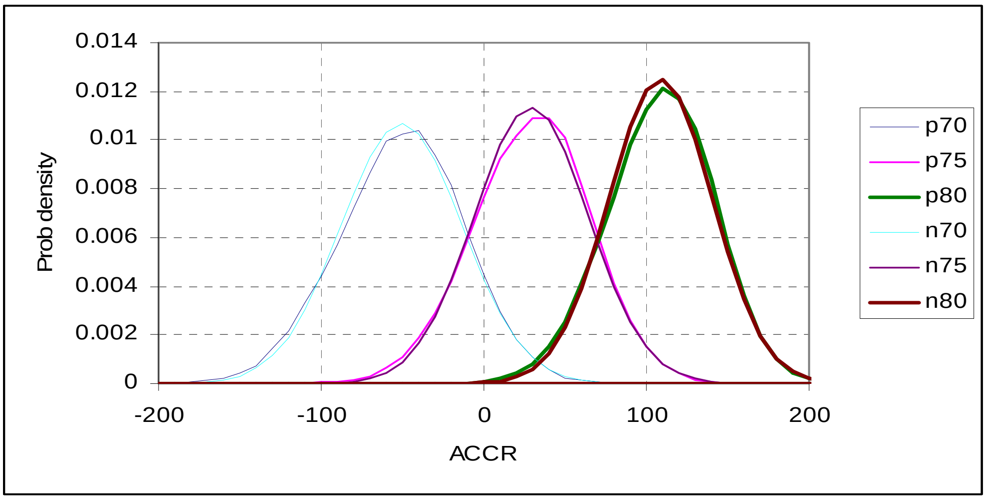

Figure 2 Estimated probability density with approximating normal density of the distribution of ACCR return for UDS-trading in AGL at skill levels of 70%, 75% and 80% respectively with brokerage at 0,5% and 20% margin

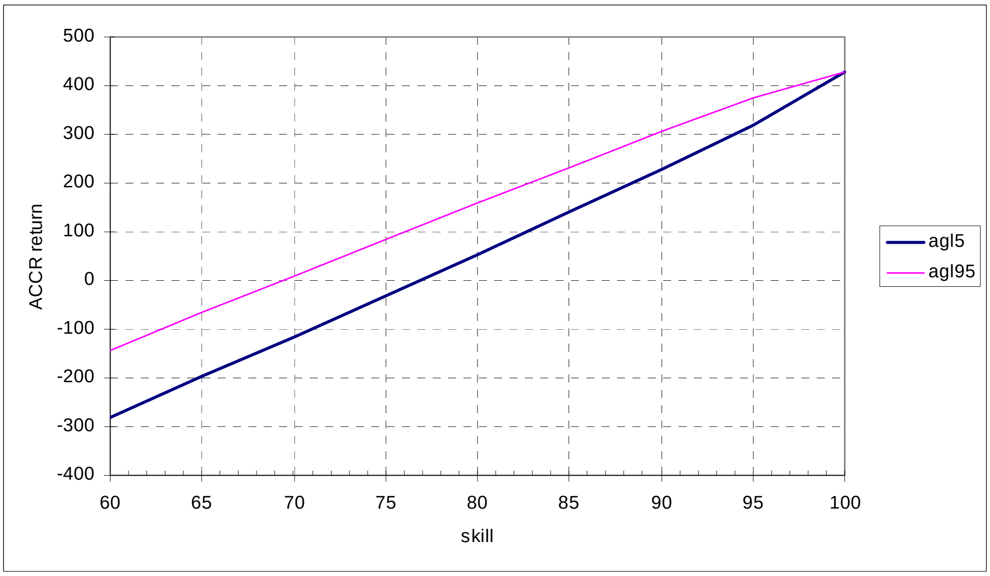

Figure 3: Estimated 5th and 95th percentiles of the distribution of ACCR returns as functions of skill level when trading in AGL with 0,5% brokerage and 20% margin

Table 4: CSLs at 95% confidence for UDS-trading with 20% margin

	c=0,00%		c=0,25%		c=0,50%		c=0,75%		c=1,00%	
share	CSLL	CSLH	CSLL	CSLH	CSLL	CSLH	CSLL	CSLH	CSLL	CSLH
AGL	48,6	56,0	54,0	62,6	69,4	76,8	85,2	89,9	93,5	96,2
BIL	48,4	55,9	54,3	62,9	70,4	77,6	85,9	90,5	93,9	96,4
SAB	48,0	55,5	56,8	65,3	78,4	84,4	92,4	95,4	97,6	98,6
RCH	48,2	55,7	55,1	63,8	72,5	79,3	88,0	92,1	95,1	97,3
AMS	49,4	56,8	52,4	60,7	60,3	68,7	72,1	78,9	83,2	88,3
MTN	49,1	56,4	52,6	61,1	62,9	71,0	76,9	83,1	87,6	91,8
SOL	48,8	56,3	52,8	61,6	65,3	73,2	80,5	86,0	90,2	93,8
SBK	48,5	55,9	53,8	62,3	69,9	77,0	85,9	90,4	94,0	96,6
OML	48,2	55,6	55,2	63,7	73,7	80,4	89,0	92,9	95,9	97,7
FSR	48,8	55,9	55,3	63,7	70,9	78,2	86,7	91,1	94,4	96,8

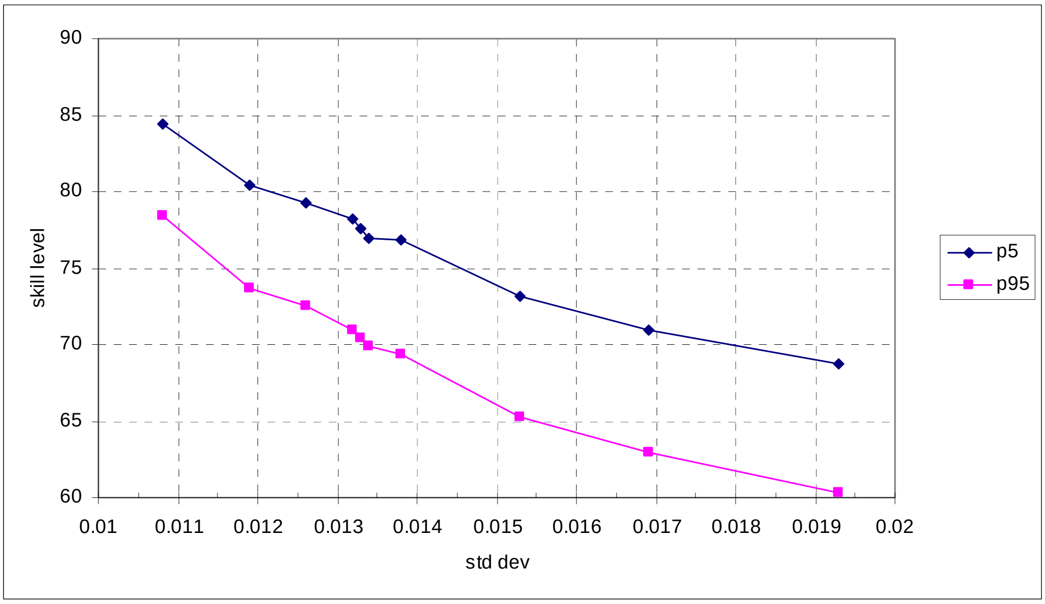

Figure 4: CSLs at 95% confidence for UDS-trading at different standard deviations with 0,5% brokerage and 20% margin

At brokerage of 0,25% Table 4 shows that a skill level in the low 60% range will be sufficient to ensure success with high probability. This may seem easy but keep in mind that the UDS trader needs to choose from three possibilities every day. If he was merely guessing his skill level would only be 33,3% which is far from the required 60% range. His methodology will need to have real (but not necessarily perfect) predictive power.

4.4 CFD trading with imperfect skill: UD trading

Perhaps the weakest link in the analysis above is the assumptions leading to equations (6) and (7). These assumptions were necessitated by the fact that there are two possible choices with different actions that can be taken when the trader is wrong. The situation is simpler if we look at a UD-trader. In this case there is only one action when he is wrong and the need for additional assumptions to disentangle the probabilities of the two possibilities falls away. More precisely, assume that on a positive return day, the trade either takes a long CFD (with probability p and correct but only profitable if the return is large enough) or a short CFD (with probability $1-p$ and completely incorrect and unprofitable). On a negative return day, he either takes a short CFD (with probability p and correct but only profitable if the return is negative enough) or a long CFD (with probability $1-p$ and completely incorrect and unprofitable).

Simulation under these assumptions is similar to (and simpler than) that reported in the previous paragraph. Table 5 shows the CSLs at 95% confidence for this case. At zero brokerage there is, of course, no difference between UD- and UDS-trading and the corresponding columns of Tables 4 and 5 are the same. Since even the UD-oracle was not able to survive when brokerage is above 0,5%, we restricted attention to brokerages of 0,5% and lower here. At brokerage of 0,5% the UD-oracle did not survive when trading in the less volatile shares and this is reflected by the CSLs shown for these shares indicated by "-".

When the brokerage is not zero the CSLs required for UD-trading are higher than for UDS-trading. This is to be expected since there are then more sources of losses. Even when he correctly anticipates a positive (negative) return day, he may lose if the return is not positive (negative) enough. As with UDS-trading higher volatility again helps with UD-trading in the sense that lower critical skill levels are required to avoid ruin or to guarantee success. At brokerage of 0,25% skill levels in the high 70% range are required for success with the volatile shares and in the low 80% range for the less volatile shares. Keep in mind that the UD-trader who is merely guessing has a skill level of 50% since only two choices are involved. So substantially higher skill is required for success and again his methodology will require real predictive power.

All graphs and tables so far were calculated at the margin rate of 20%. Margins as low as 10% often occur in practice and the results were recalculated at this value. By way of illustration Table 6 gives the CSLs for the same case as Table 5 except that now $m = 10\% = 0{,}1$. In all cases they are similar to, but slightly higher, than those of Table 5. It appears that the higher risks implied by trading at higher gearing ratios require higher levels of skill to guarantee the same probabilities of avoiding ruin and achieving success.

Over the time period of this study the JSE experienced a bull market, with all shares trending upwards. Are the results reported above influenced by this trend? One way to look into this matter is to carry out the simulation backwards in time with the daily returns reversed in sign. This will simulate trading under a bear market of the same magnitude as the actual bull market. We repeated the studies above in this way and found that the results were virtually the same as those reported above. This confirms that longer term market trends have little influence on CFD day trading performance, contrasting strongly with volatility which is beneficial for this form of trading.

4.5 Using a stop loss strategy

Stop losses are often employed in an effort to control trading risk. Could stop losses be used beneficially in our context? To study this question by simulation, we extended the VWAP calculations from only the first and last hour to include also the second, third, ... , seventh hour for every trading day. From these we obtained the VWAP returns from the first to the second hour, first to third hour, etc. We then allowed the trader to follow the hourly returns on his position taken in the first hour and to bail out (at the VWAP of that hour) as soon as his trade return is more negative than a given stop loss level. Rerunning the simulations in this way we estimated the CSLs with stop losses employed as part of the trading process. Table 7 illustrates typical results for the case of UD-trading with brokerage at $c = 0{,}25\%$, margin at $m = 0{,}1$ and with stop loss levels absent or at 20%, 10% and 5%. As is to be expected at the high level of 20% there are practically no differences between the CSLs when stop losses are absent or present. With the more stringent stop loss level of 10% the CSLs increase somewhat and with an even more stringent level of 5% the CSLs increase even further. Thus it appears that stop losses are of little value in this situation.

4.6 The impact of skills levels on capital losses

Finally consider the question: how quickly would a trader with too low a skill level lose his capital? To get quantitative results on this question we need to define first what "losing his capital" means. On every losing trade only a (positive) fraction of the capital is lost, not everything. So strictly speaking capital never reduces to absolutely zero. Therefore we need some cut-off value which is effectively equivalent to ruin and we shall assume that the loss of 99% of the initial capital is appropriate for this purpose. In the course of simulation we can record the first time when the trader's capital drops below 1% of its initial value. This time is also a random variable and the 95% percentile of its distribution (call this T_{95}) tells us that the trader will have lost 99% of his capital by time T_{95} with 95% probability. Table 8 illustrates with the results for the case of UD-trading with $c = 0{,}25\%$ and $m = 0{,}2$ at different skill levels. The entries marked by "-" correspond to cases where this loss event did not occur before the end of the 848 days of the study and the skill levels were high enough to avoid ruin. At skill level of 50% the trader will lose 99% of his capital in less than one trading year with 95% certainty. It takes longer for this event to occur at skill levels of 55% and 60% and for the more volatile shares (e.g. with AMS the trader may survive up to two years). At even higher skill levels the trader survives the full period, and as seen previously, may well flourish. As expected, at higher (lower) brokerage rates ruin occurs sooner (later) at the low skill levels than those shown in Table 8.

Table 5: CSLs at 95% confidence for UD-trading with 20% margin

	c=0,00%		c=0,25%		c=0,50%	
share	CSLL	CSLH	CSLL	CSLH	CSLL	CSLH
AGL	48,6	56,0	72,5	78,8	99,1	99,5
BIL	48,4	55,9	73,3	79,5	-	-
SAB	48,0	55,5	79,1	84,8	-	-
RCH	48,2	55,7	74,5	80,7	-	-
AMS	49,4	56,8	66,2	73,0	85,2	90,2
MTN	49,1	56,4	68,5	75,1	89,8	93,8
SOL	48,8	56,3	70,6	77,3	94,5	97,2
SBK	48,5	55,9	73,2	79,5	-	-
OML	48,2	55,6	75,8	81,7	-	-
FSR	48,8	55,9	73,4	79,6	-	-

Table 6: CSLs at 95% confidence for UD-trading with 10% margin

	c=0,00%		c=0,25%		c=0,50%	
share	CSLL	CSLH	CSLL	CSLH	CSLL	CSLH
AGL	50,8	58,3	74,4	80,6	99,1	99,5
BIL	50,7	58,0	75,1	81,3	-	-
SAB	49,9	57,4	80,7	86,0	-	-
RCH	50,7	57,9	76,3	82,3	-	-
AMS	52,8	60,3	69,2	75,9	85,2	90,2
MTN	52,0	59,5	71,0	77,5	89,8	93,8
SOL	51,5	59,1	73,0	79,5	94,5	97,2
SBK	50,8	58,2	75,0	81,2	-	-
OML	50,2	57,6	77,3	83,2	-	-
FSR	50,8	58,2	75,2	81,4	-	-

Table 7: CSLs at 95% confidence for UD-trading with 0,25% brokerage, 10% margin and varying stop loss levels

	No stop loss		Stop loss 20%		Stop loss 10%		Stop loss 5%	
share	CSLL	CSLH	CSLL	CSLH	CSLL	CSLH	CSLL	CSLH
AGL	74,4	80,6	74,0	79,8	76,3	82,0	83,7	89,3
BIL	75,1	81,3	75,2	81,1	79,2	84,7	86,2	91,5
SAB	80,7	86,0	80,5	85,9	79,1	84,8	95,0	97,7
RCH	76,3	82,3	76,3	82,1	82,7	87,7	89,9	94,5
AMS	69,2	75,9	68,5	74,8	69,8	76,2	73,9	81,0
MTN	71,0	77,5	70,7	76,8	72,5	78,9	76,6	83,2
SOL	73,0	79,5	72,0	78,2	73,6	79,8	79,4	85,7
SBK	75,0	81,2	74,8	80,7	77,1	82,9	84,0	89,5
OML	77,3	83,2	77,0	82,8	79,7	85,0	89,9	94,3
FSR	75,2	81,4	75,6	81,4	79,1	84,7	86,8	91,9

Table 8: Time in trading days to lose 99% of capital with 95% probability at different skills for UD-trading with 0,25% brokerage and 20% margin

share	p50	p55	p60	p65	p70	p75	p80
AGL	231	298	416	601	-	-	-
BIL	234	296	414	592	-	-	-
SAB	222	274	346	446	615	-	-
RCH	230	302	407	564	-	-	-
AMS	233	331	506	-	-	-	-
MTN	228	312	445	-	-	-	-
SOL	230	298	427	673	-	-	-
SBK	227	287	375	561	-	-	-
OML	231	296	391	537	-	-	-
FSR	224	278	358	513	-	-	-

5. SUMMARY AND CONCLUSION

Short term returns on stocks are usually quite small and this is especially true for intraday trades. It is therefore tempting to use derivative type trading methods that provide gearing to the underlying price movements in order to enhance short term returns. CFD trading is particularly popular in this regard. Indeed, CFD trades already account for more than 20% of trades on the London Stock Exchange and have a rapidly rising impact on other exchanges as well (Gunnion, 2007). CFD trading providers usually demonstrate the effectiveness of this form of trading by showing the large gearing obtained from in the money CFD trades while also posting "wealth warnings" in terms of potential losses from out of the money CFD trades (e.g. http://www.nedbank.co.za/website/content/cfd/index.asp). Missing elements required for a balanced assessment of the value of CFD trading are the impacts of skill levels and brokerage rates on the returns obtainable from CFD trading. Although Internet searches yield many sources of information on CFD trading, we are unable to find pertinent published results on these missing elements. The existing literature on market timing does provide quantitative results on these issues for longer term trading with long only portfolios. This paper extends those results to the present context, thus filling this gap to some extent.

Brokerage rates are taken into account explicitly by developing formulas that express the CFD trade return in terms of the return of the share and the brokerage rate. It turns out that the CFD gearing operates on both these factors. This makes the eventual outcome of CFD trading extremely sensitive to the brokerage rate. Further, we modeled the trader's decision methodology in terms of simple probabilistic assumptions so that we can measure his skill by his probability of taking correct positions and we evaluated the financial consequences by means of simulation studies using empirical intraday data from trading on the JSE. It turned out that the critical skill levels needed to avoid ruin and to ensure successful CFD day trading with high degrees of confidence are generally quite high, especially when compared to random guessing. It also turned out that these requirements are somewhat less stringent when trading in highly volatile shares but that the systematic use of stop losses yielded little benefit in this context.

In risk-reward terms, the results indicate that the trader with skill below the CSLL carries large risk with little hope of any reward. With skill above the CSLH the trader has prospects of large rewards accompanied by little risk. With skill level between CSLL and CSLH, risk and reward are simultaneously not negligible and would suggest the need for studying them in terms of risk-reward efficient frontiers. We have not done so here and leave this for future research. Further studies on trading rules, using completely specified methods of predicting share price movements and rules based on the occurrence of share price and volume events, can be carried out in this framework; and is another area for further research. Simulation studies are inherently limited in terms of the amount of understanding that they can deliver. It is therefore desirable to also develop analytical approaches that may help to clarify the empirical results reported here.

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