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The performance of amateur traders on a public internet site: a case of a stock-exchange contest

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Abstract

This paper studies a very thorough e-trading data base, including all of the bid/ask orders and daily portfolio values of more than 600 on-line amateur traders in the Paris Stock market focusing on the stormy period covering 2007-2009. Traders also participate in a monthly contest and can win significant prizes. Our first result emphasizes the huge average losses of amateur traders. On average, portfolio values fall from an initial value of 100 to a terminal value of 7 in the 29 months covered here. Our final value is 28 including rewards. The second result is more surprising. Despite our splitting context, smart traders don't clearly emerge. There is clearly no performance persistence, neither for winners nor for loser. With a very few exceptions, winners seem to be just lucky not skilled.

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1. **Introduction**

This paper studies a very thorough e-trading data base, including all of the bid/ask orders and daily portfolio values of more than 600 on-line amateur traders in the Paris Stock market. Traders also participate in a monthly contest and can win significant prizes, up to 10000 Euros, associated with relatively small initial outlays. Investors can bet on few assets and have high leverage in order to win the prizes. Moreover, thanks to its specific delayed payment service, the Paris Stock market offers cheap and easy ways to leverage and short sell. Hence, calamitous management of a bearish reversal market can't be due neither to technical constraints nor to costs to take short positions.

By focusing on the stormy period covering 2007-2009, the paper may challenge the usual stylized fact of a stock market composed of smart vs. foolish investors. Foolish (unskilled) trader's performances should be sharply different from those of smart (skilled) traders in such a volatile period characterized by sudden reversals of market valuations. This divergence of performances should be amplified by the contest situation which clearly encourages traders to undertake risky behaviors.

Our first result emphasizes the huge average losses of amateur traders. Although this result is not new, we observe very more drastic losses relative to previous studies on amateur traders (Anderson, 2006, Barber and Alii, 2004, Choi, Laibson, Metrick, 2002, Barber, Odean, 2001, Dom, Sengmueller, 2009, Mizrach and Weertz, 2009). On average, portfolio values fall from an initial value of 100 to a terminal value of 7 in the 29 months covered here. Our final value is 28 including rewards. The second result is more surprising. Despite our splitting context, smart traders don't clearly emerge. As quoted by Shiller 2003, "If we have data on individual trades and if some people are smarter than others at trading, then we should find that some people persistently lose money while others persistently make money". There is clearly no performance persistence, neither for winners nor for loser. With a very few exceptions, winners seem to be just lucky not skilled. This clearly differs from other studies like Barber and Alii, 2004 (Taiwanese day traders) or Mizrach and Weerts (2009). So we are constrained to throw in the sponge and admit that there are only foolish traders in our sample. If smart investors exist they are not in our sample.

2.Description of the database and the contest

Zonebourse is a stock exchange Internet site which has since February 2007 proposed two trading contests each month. Participants can take part in the first, a stock contest, by trading an authorized list of 281 stocks (close to the SBF250). Participants can also compete in a second, Warrant, contest. 20,000 Euros are paid out each month for each contest. The minimum initial investment is only 1000 Euros, so the contest is very attractive. In return, each investor accepts the total transparency of their operations which are freely available on-line for both other participants and visitors to the site.

The participants in the stock contest can benefit from the SRD (Delayed Payment Service) of the Parisian Stock Exchange. The SRD thus permits participants to open short positions and to obtain leverage while trading on stocks, without being obliged to trade with derivatives (options, warrants or futures). Moreover, transaction fee is 0.12% of the transaction amount, with a minimum of 8.97€ per order and 17.94€ for a round trip. The average round trip is 24.50€ for an average transaction of 1265€, so that fees represent around 2% of the total transaction amount.

The data we analyze, provided by Zonebourse, are collected on 5 Excell files: Participants file; Flows file with contributions and withdrawals of currency and securities; An Orders file; A Transactions file with the hour, date and price of entry and exit, and quantities;

A Portfolio Value file which identifies the value of the portfolio of each participant each day, profits and losses on the SRD, the value of stocks, cash, contributions and withdrawals.

688 traders were active during this period, and have their operations recorded in the data base. At the 06/16/2009 closing date, 586 traders were still active.

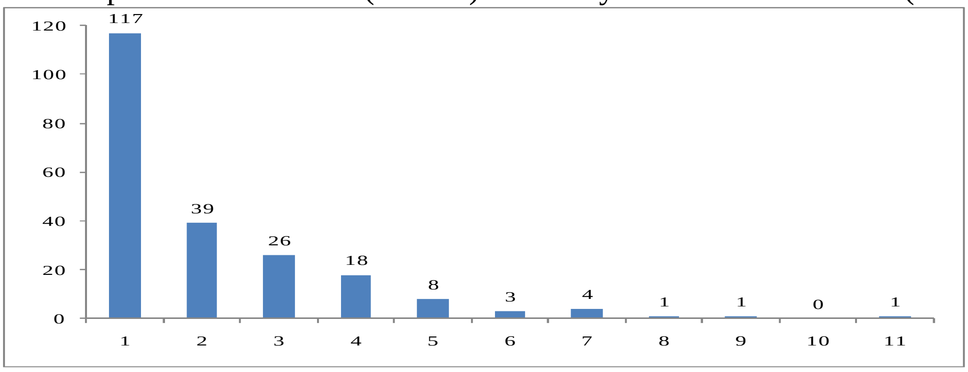
During the period under consideration, 459 rewards were distributed amongst 218 traders. The reward ratio is the value of the reward divided by the value of the portfolio. The last column of Table 1 shows that rewards double the portfolio value of winners on average.

Table 1: Number and value of rewards for winners:

	Number of rewards	Portfolio value	Value of rewards	Reward ratio
Mean	2.11	2370.12	1746.50	0.99
Std deviation	1.66	2458.51	2211.61	1.42

The distribution of rewards is concentrated since only 116 winning traders win more than 1000 Euros. Nevertheless, 40 winners win at least 10000 Euros.

Figure 1: Population of winners (Y-Axis) ranked by number of times won (X-Axis)



Positions are open for an average of four days. The median position duration is 0.7 days, and 75% of positions are open for less than three days. Day traders are hence frequently observed in the contest. 73% of positions are long and 27% are short, and 70% of positions are open on the SRD. The median portfolio value is 1700€. However, the portfolio value when positions are held is 4702€. Leverage is high in this data: mean leverage is 1.79.

3.Performances

3.1. Method 1: mean annualized performance rates

We now want to calculate the Dietz (1968) performance rate from the portfolio-value data file. These performances are net of transaction fees, which are recorded as negative contributions. Performances are calculated from the change in portfolio value, *i.e.* the sum of the cash, SRD portfolio and stock portfolio values. We adjust these values for contributions and withdrawals in order to obtain the daily net performance of a trader's portfolio. Performance over a period (week, month or year) is simply the ratio of the adjusted closing portfolio value to the adjusted opening value. Traders are present for varying periods of time. To compare results across individuals, we thus require a mean annualized performance rate. For traders who were active for less than one year, this assumes that profitability can be extrapolated to a whole year. In some cases of very good results, this led to disproportionately high extrapolated figures. For example, a trader who multiplied her capital by a factor of 10 in a little over 2 months is allotted an imputed annual performance of over 6000 times her start-up capital. These kinds of extreme values are eliminated (by dropping the first and last percentile of results) as they introduce too much skew in mean performance. Following financial tradition, annualized relative outputs are the difference between the trader's annualized output and that of the market (SBF250)): R-Rm. This is what we simply call performance below.

Table 2: Annualized idiosyncratic performances statistics (method 1)

	Duration (days)	Start-up capital	Contributions	Performance %
Average	482.67	2628.93	6946.77	-38
St. Dev.	261.23	4601.18	19344.13	66
Quantiles				
0.1	125.30	1000.00	1000.00	-90
0.5	473.50	1125.00	2650.00	-52
0.75	753.00	2000.00	6000.00	-13
0.8	790.00	2500.00	7500.00	-2
0.9	825.00	5000.00	13000.00	21
0.95	839.00	10000.00	21931.50	35

Traders' results are much worse than that of the SBF 250, with amateurs having an average annual performance of -38%. Only the top two deciles of traders beat the market. Note that the annualized performance of the SBF 250 is -20.9%. The average annualized performance of traders is thus around -59%. These results are robust to eliminating the traders who are present for less than 6 months. The share of relative winners is close to that in previous work such as Anderson (2006), where only a quarter of investors enjoy positive gains. We have 17 Traders (and another 6 in the eliminated first percentile) who are “stars”, beating the market by more than 100% annualized. Around 5% (6% with the top percentile) beat the market by over 35%. At the other end of the distribution 10% (11% with the bottom percentile) lose more than 90% annualized relative to the market.

Including rewards yields higher average performance figures (after eliminating extreme percentiles) of -13%. However, again only two deciles beat the market (performance is below 5% for the bottom 8 deciles). Better performances are found for the top decile (31%) and the top 5% (128%).

3.2 Method 2: random investment model

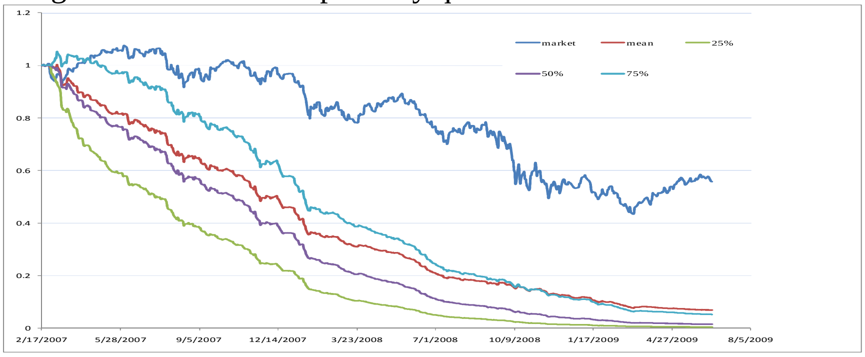
Traders are not all present or active over the same periods. This heuristic difficulty can be treated via a random investment model, in which each day traders are randomly drawn using a standard Monte Carlo method. A random performance path over the period is then computed. For each set of dated draws, we obtain a random investment performance over the period. With an initial portfolio value of 100 we can calculate the value of the portfolio at the end of the period for a given path of random draws. These Monte Carlo draws are repeated one million times: the resulting statistics appear in Table 3.

Table 3: Final portfolio distribution with random investment

Quantile	Market	Mean	25%	50%	75%	90%	95%	97.5%	99%	99.9%
Final Portfolio (Starting=100)	55.73	6.84	0.42	1.55	5.27	14.94	27.55	44.47	88.84	260.47

Random investment leads to quasi-ruin for at least 75% of the randomly-drawn paths.

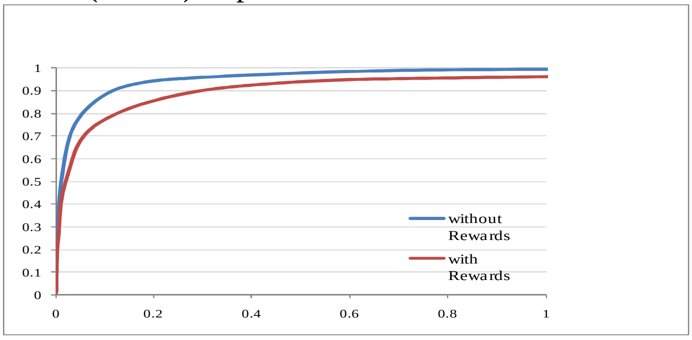
Figure 2: Performance paths by quartiles



This figure shows that the results are far from brilliant even if the investor is very lucky and draws each day the first decile or percentile of the best traders. Random investment thus leads to drastically bad results; we have to admit that the performance of our sample is very disappointing, and is worse than that found in the previous literature on internet amateurs, (Barber and Odean, 2001, Dorn, Sengmueller, 2009 and Mizrach and Weertz, 2009). However, our period is not the same (covering the 2008 financial crisis) and our contest situation may well also exacerbate losses.

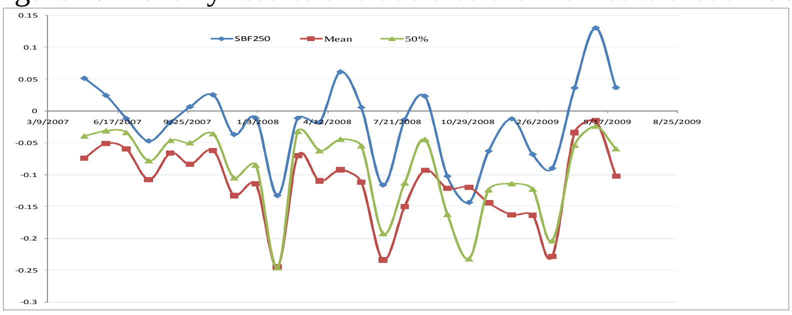
With rewards, the mean final value is significantly higher, 28.3, than that without rewards. This reflects some good performances from the best winner traders, but, clearly, gains are not so good for the majority of traders. Even with rewards, 95% of traders still record losses.

Figure 3: The distribution (Y-axis) of portfolio final values with/without rewards (X-axis)



It can be argued that these bad results reflect the 2008 financial crisis, *i.e.* a strong bearish stock market. However, our period also covers some bullish moments. To test the effect of market period on the amateur traders' results we carry out a historical analysis: we compute the mean monthly performance of traders and compare this to that of the market. Figure 4 shows that traders' monthly performances are always worse than that of the market: their losses are amplified, and their gains are smaller.

Figure 4: Monthly results of traders vs the Market without inactive traders



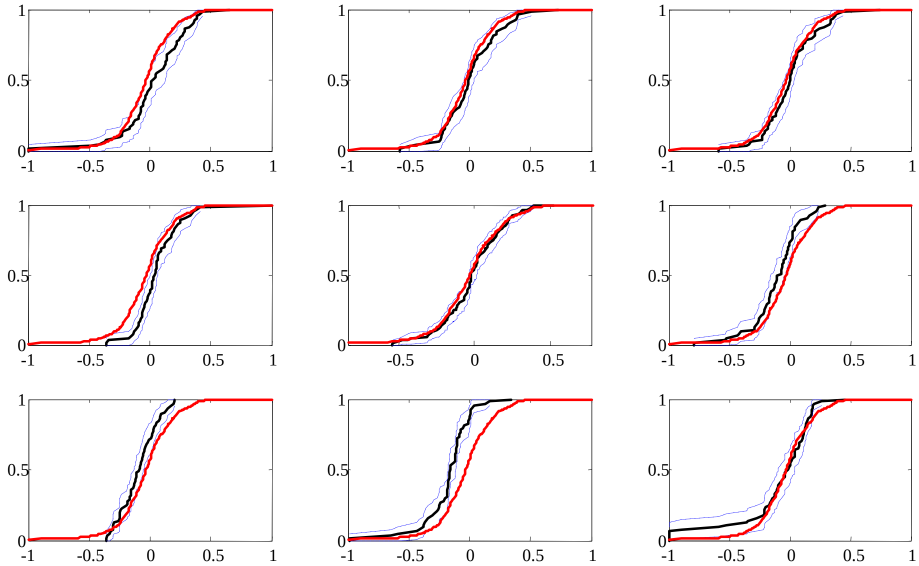
4. Is there persistence in results?

One classic question regarding trader performance is their ability to persistently enjoy excess returns. Intuition suggests that lucky traders will not report persistently good results, while good traders will do so: luck is only short-run. There should therefore be a relation between performance and autocorrelation: is this the case?

4.1. The distribution of autocorrelation by trader rank

We examine the link between performance and persistence by ranking traders in 10 mean weekly performance deciles. We then test the hypothesis that the Empirical Cumulative Distribution Function of the Autocorrelation coefficients (for lags comprised between 1 and 12) is the same across deciles. We use the Kolmogorov-Smirnov (K-S) goodness-of-fit test. Only lag 1 produces a KS test difference for 2 deciles.

Figure 4[1]: ECDFA lag +1 for each decile vs mean ECDFA and confidence interval



Only deciles 4 and 9 are different from the entire population distribution. Decile 4 ECDFA is closer to the no-autocorrelation distribution, given by the vertical at 0, so there is clearly less persistence than in the entire population. The decile 9 ECDFA is rather more negative than that for the entire population. This result is unexpected since this decile has better results than average. This suggests the absence of any positive persistence of good results among even (relatively) good traders. As such, the previous week's performance has no (or a negative) impact on the next week's performance. This suggests the absence of skill among traders, even for those who have the best performances. Are the best traders just lucky?

3.2. Transition analysis

The previous test appeals to the autocorrelation between weekly mean returns. Another approach is to consider the relative ranks of the competitors. We thus rank traders each month into 10 deciles. We then use the date to calculate the transition probability from one decile to another (the Markov transition matrix). In each month, this transition matrix is

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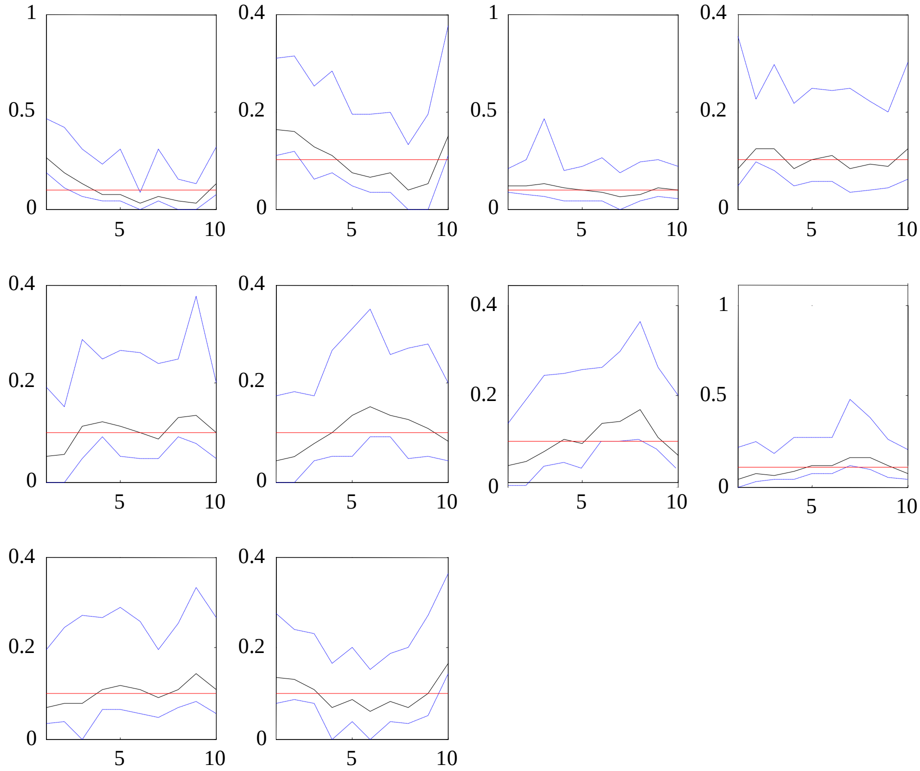
[1] The black line in each plot is the ECDFA of each decile (deciles 5 and 6 are merged). The deciles are increasingly ranked from decile 1 (worst performances) in the North-West to decile 10 (best performances) in the South-East. The two blue dotted curves are the 5% confidence intervals. The red curve is the entire population ECDFA.

considered as a random draw. Hence, we construct the statistics over the sample of the frequencies for each decile and obtain the matrix of the mean transition frequency and the associated 90% confidence intervals.

Figure 5[2]: The mean frequencies of transitions from deciles 1 to 10



The figure should be read as follows: for the tenth decile, for instance, the mean frequency of being in a given decile the next month is given by the black line. If there were no persistence, the frequency would be 0.1 for all deciles (the red line), the equi-probability. We note that being in the top decile (the winners) in a given period favors being in this decile the next period, slightly. However, the associated probability of being in the first three deciles (the losers) is also over 10%. Persistence amongst good traders is thus far from being clear.

From another perspective, we have considered the frequency of a trader in a given decile to stay in the same decile the following month. This persistence seems to be stronger for losers (over 25%) than winners (15% in the last 4 deciles). To evaluate the frequency of being in the same decile during the N next periods (a long-term analysis), we use a Monte Carlo method. We simulate the decile paths implied by our Markovian matrix. We then compute the implied expected frequency of being in the same decile.

In Table 4, the expected frequency for every T is close to both the equi-probability of the uniform distribution and the ergodic probabilities of the transition matrix. We thus confirm the previous finding that decile persistence in the ranking is fairly weak.

[2] The two blue dotted lines show the 90% confidence intervals.

Table 4: Expected frequency of being in the same decile in the next periods

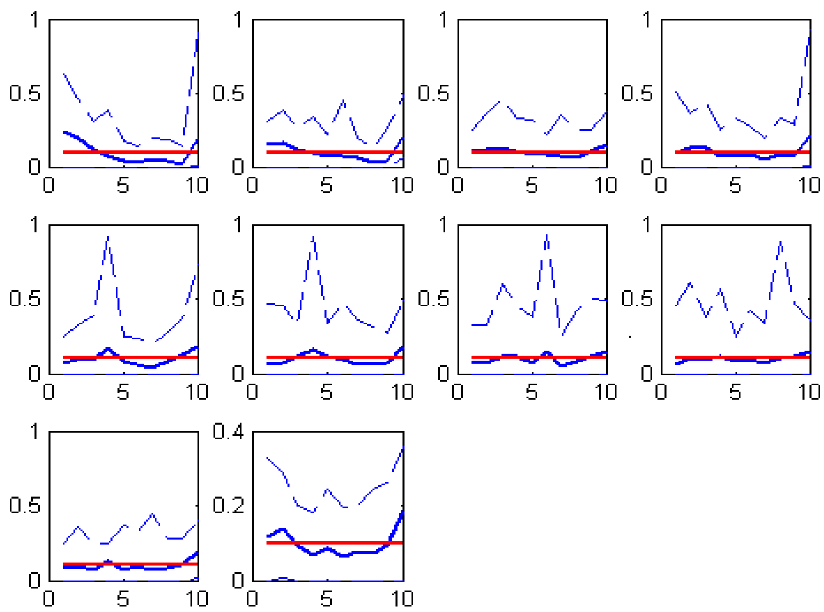
deciles	1 year	2 years	3 years	5 years	10 years	ergodic prob
1	11.85%	11.05%	10.68%	10.50%	10.32%	10.11%
2	11.05%	10.59%	10.55%	10.41%	10.40%	10.32%
3	10.40%	10.45%	10.37%	10.35%	10.32%	10.27%
4	9.46%	9.51%	9.55%	9.52%	9.51%	9.51%
5	9.97%	9.99%	9.85%	9.97%	9.94%	9.88%
6	10.11%	9.79%	9.87%	9.65%	9.63%	9.57%
7	10.36%	9.99%	9.85%	9.85%	9.76%	9.75%
8	10.49%	10.18%	10.06%	10.00%	9.94%	9.87%
9	10.38%	10.15%	10.06%	9.90%	9.86%	9.85%
10	11.37%	11.04%	10.96%	10.90%	10.91%	10.81%

3.3) Is there a stars' bias?

The previous analysis has provided only little support for skill-based explanations of trading success. This may be the case because there are so few skilled traders that the final decile analysis is not restrictive enough. We thus extract the star traders from the data and calculate their transition matrix over the 10 deciles (defined for all competitors). Star traders are defined as those who win prizes at least once, twice, or three or more times.

We present below the mean transition frequencies for each decile. These show the following-month decile of star traders. Of course the confidence intervals are now very wide, but the results are surprising in that there is no salient difference from the previous decile analysis.

Figure 6: The mean frequency of transitions from decile 1 to 10 for winners



The long-term analysis is however more supportive of a skill effect:

Figure 7: Probability of staying in the top decile the next month

Table 6 : Long-term analysis with ergodic probabilities (%)

deciles	hazard	population	≥1 prize	≥2 prizes	≥3 prizes
1	10	10.1	11.4	12.8	12.2
2	10	10.3	12.5	13.0	11.4
3	10	10.3	10.9	10.8	11
4	10	9.5	10.4	10.2	9.2
5	10	9.9	7.8	8.3	8.3
6	10	9.6	7.5	5.5	6
7	10	9.8	6.2	4.8	5.1
8	10	9.9	6.7	5.4	5.3
9	10	9.9	8.1	7.5	76
10	10	10.8	18.4	21.9	24

The long-term ergodic probability for the tenth decile thus is clearly different from the equi-probability, with rapid convergence. We thus find a star effect for prize winners.

5.Conclusion

While 1% of traders are “stars”, who clearly win a great deal relative to the market, more than 80% of traders lose relative to the market. In absolute, more than 99% of traders lose and face drastic losses. On average, portfolio values fall from an initial value of 100 to a terminal value of 7 in the 29 months covered here. The final value is 28 including rewards. There is no clear performance persistence for traders. Are the best traders just lucky then? Focusing on contest winners, the long-term transition analysis suggests a long-term probability of staying in the best decile which is greater than the chance. We thus cannot reject a “star effect”. Online trading may just be costly entertainment, like casino gambling.

6.References

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