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

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Abstract:

We analyze a very thorough data base, including all of the bid/ask orders and daily portfolio values of more than 600 on-line amateur traders from February 2007 to June 2009. These traders were taking part in a stock-exchange contest proposed by the French Internet stock-exchange site Zonebourse. More than 80% of traders lose relative to the market. Their relative average annual performance varies from -38% to -60%, depending on the method used. 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. When we include the rewards offered by the contest, average performance becomes -13% a year. However, only two deciles continue to beat the market. From an initial value of 100 the final value is 28 including rewards, but 95% of traders still lose in absolute. 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 chance. We thus cannot reject a “star effect” of staying in the best decile. However, the great majority of amateurs do seem to be e-pigeons. Online trading may just be costly entertainment, like casino gambling.

In this paper, we analyze a very thorough data base, including all of the bid/ask orders and daily portfolio values of more than 600 on-line amateur traders. These traders were taking part in a stock-exchange contest proposed by the French Internet stock-exchange site Zonebourse. These data are available from February 2007 to June 2009, so that the period under consideration covers the 2007-2008 subprime crisis. The behavior and performances of amateur traders on the internet is of considerable interest. In January 2010, amateurs carried out more than one million orders on the Parisian market and held more than one million client accounts. On-line trading accounted for 11%[1] of orders passed on the Paris exchange. The behavior of amateurs may have serious consequences for equilibrium in the financial market, particularly if they are "irrational".

Both professionals and academics are interested in these behaviors. The first consider the possibility of being able to "money pump"[2] such irrational or badly-informed agents; the latter analyze the economic performance and behavioral biases of amateurs *per se*.

The performance of amateurs can reveal whether trading is really a job or not. If so, it requires specific skills or experience. Professionals would then be expected to have better performances than amateurs; not only because they are better informed or lucky, but also because they are less inclined than amateurs to succumb to behavioral biases. In the context of trading, these biases have been well-described in previous work in behavioral finance: the *momentum* bias (Jegadeesh and Titman, 1993), the disposition effect (Shefrin and Statman, 1985), overconfidence (Alpert and Raiffa, 1982), insufficient diversification, casino gambling behavior, and so on.

With respect to the skill effect, Mizrach and Weerts (2009) showed, in their work on amateur traders, that experience matters: traders who have been present on the market longer enjoy better results. They interpret their results in terms of a "learning by trading effect".

[1] The market share of brokers who are on-line members of ACSEL, the French association of digital economics.
[2] See Cubitt and Sugden (2001) for a discussion of money pumps, Dutch booking, and deviations from standard consistency assumptions.

These behavioral biases can be exacerbated by trading on-line, since the latter accelerates the speed of reaction of those who trade from home, and can lead individual investors to carry out too many transactions. Barber and Odean (2000, 2002) and Odean (1999) have shown that investors who are overconfident carry out too many transactions, and that by doing so they reduce their expected profits. The beginning of online trading, at the end of the 1990s, has clearly boosted the number of orders (Choi, Laibson, Metrick, 2002), but led to a fall in trader profitability (Barber and Odean, 2002).

Last but not least, our database provides heuristic materials in a real market situation where the contest situation (traders can win significant prizes of up to 10000 Euros) is associated with relatively (to agents' total wealth) small initial outlays. Traders thus have incentives to take undiversified risks, bet on few assets, and have high leverage, in order to win the prizes. Even if they often lose ex post, the expected ex ante reward encourages risk taking. Dom and Sengmueller (2009) have already argued that online trading can be considered as entertainment, and Anderson (2006) considers online trading as casino gambling, where the great majority loses and a few win. Our contest situation may exacerbate this gambling aspect.

In this paper, we analyze the performance of these amateur traders and then focus on the persistence in performance to identify an eventual skill effect. As previously suggested, amateurism, the speed of transactions and the contest situation should lead to drastic losses for our amateurs. We will see whether our data vindicate this pessimistic prediction. Are online traders really just e-pigeons (Blanchard, 2000)? Moreover, is there a skill effect for the best traders (persistence) or are they just lucky?

The first section below presents our database, the contest, the Parisian stock market and descriptive statistics. We then examine the distribution of trader performances, the timing of these performances, and their distribution by age and gender. Section 3 then examines the persistence of performance over time. Last, Section 4 concludes.

1) DESCRIPTION OF THE DATABASE AND THE CONTEST

1.1) 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) with a maximum leverage effect of 3. Participants can also compete in a second, Warrant, contest. Since January 2009, only the Warrants emitted by Commerzbank, which is Zonebourse's partner, are permitted in the contest. Previously, the investors had to hold at least one Commerzbank Warrant. 20,000 Euros are paid out each month for each contest.

Table 1: Monthly Prizes

Monthly ranking	Stock contest rewards (€)	Warrant contest rewards(€)
1^{st}	10000	10000
2^{nd}	4000	4000
3^{rd}	2000	2000
4^{th}	800	800
5^{th}	700	700
6^{th} -10^{th}	500	500

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. Zonebourse is associated with the on-line broker "Bourse Direct" for stock trading and with Commerzbank for their Warrants.

Each candidate can also announce their transactions and comments on a public blog. A window continuously provides the top/flop daily performances amongst contest participants in terms of Euros won or lost, as well as their monthly and annual results.[3]

Table 2: The public window of Daily and Monthly performances

Shares			
Perf. % day	Participants	Perf. day €	Rank
+40.0%	Jetpiza	+263 €	**4** (72)
+38.6%	Evildap	+366 €	**3** (42)
+32.4%	Newbie64	+500 €	**54** (108)
-32.1%	The xav	-275 €	**133** (124)
-18.9%	Watatcho	-1399 €	**123** (90)
-13.5%	Flakettt42	-158 €	**131** (118)
Warrants			
Perf. % day	Participants	Perf. day €	Rank
+29.5%	Popolili	+97 €	**30** (45)
+24.1%	camelia	+567 €	**8** (23)
+23.8%	Traderpack	+105 €	**39** (46)
-26.1%	Parisien	-259 €	**52** (43)
-23.1%	Echo13	-400 €	**47** (38)
-21.3%	Tonio86	-205 €	**44** (34)

[3] The monthly and annual results in the window actually need to be recalculated in order to take into account contributions and withdrawals.

Classification - 12 months		Participants classified: 762 - Updated 12/10		
Rank	Participants	Perf. 12 months %	Capital	Perf. % day
1 (110)	Thefwp	+1,028.6%	4 153 €	0.0%
2 (-)	Isa000	+449.3%	741 €	0.0%
3 (8)	Jacaas	+401.0%	19 038 €	+2.3%
4 (115)	Smam77	+375.1%	971 €	-5.7%
5 (20)	Manneke	+283.0%	7 661 €	0.0%
6 (1)	Tofparis	+260.4%	7 249 €	-0.2%
7 (125)	Grindavik	+213.2%	2 116 €	0.0%
8 (39)	Snorky222	+196.0%	12 310 €	+1.6%
9 (-)	Abdess	+187.6%	2 876 €	+5.4%
10 (38)	Krylin	+167.0%	7 536 €	+6.9%

Moreover, participants' orders (and their results) are permanently posted in a window on the main page.

Table 3: Public window of orders

Date	Operation	Rank	
13/10 | 17:29	**Ginkgo**: purchase order for THOMSON	**82**	(102)
13/10 | 17:26	**Ginkgo**: closes their position on ALCATEL LUCENT	**82**	(102)
13/10 | 17:25	**Jmt454**: purchase order for KAUFMAN AND BROAD	**13**	(7)
13/10 | 17:24	**Miss daisy**: purchase order for WCSOCGE 52,13 1209		
13/10 | 17:24	**Random**: purchase order for WCSOCGE 52,13 1209	**2**	(3)
13/10 | 17:19	**Bevi**: purchase order for VALLOUREC	**56**	(-)

1.2) Paris Stock Exchange *SRD* (Delayed Payment Service)

The participants in the stock contest can benefit from the SRD (Delayed Payment Service). The SRD constitutes a distinctive feature of the Parisian Stock Exchange. For a certain number of securities published by Euronext Paris (Paris Bourse), it is possible not to settle the operation (payment for the purchases, cashing of sales) until the end of the stock-exchange month (the liquidation day). This costs an interest rate or a broker fee, which is paid to the financial intermediary. This SRD is a relic of monthly payment that was abandoned in September 2000. SBF 250 securities obligatorily have high capitalization (1 billion Euros) and a transaction volume of at least one million Euros. Cash payment remains the rule in the Paris stock exchange. SBF operations should thus be specified *ex ante*, when the order is placed.

The SRD makes it possible to benefit from leverage. The contest rules limit this leverage to a value of 3, which is lower than the level authorized by Euronext (5).

Moreover, the SRD also makes it possible to bet on the future price of a stock, and to take long or short positions with overdrafts. It is in fact possible to balance these positions only at the end of the stock-exchange month. 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).

1.3) Data Files

The data we analyze, provided by Zonebourse, are the same as the public data, but collected on 5 Excel files. The data begin on February 14th 2007 and run to June 16th 2009 (26 months). The five files are as follows.

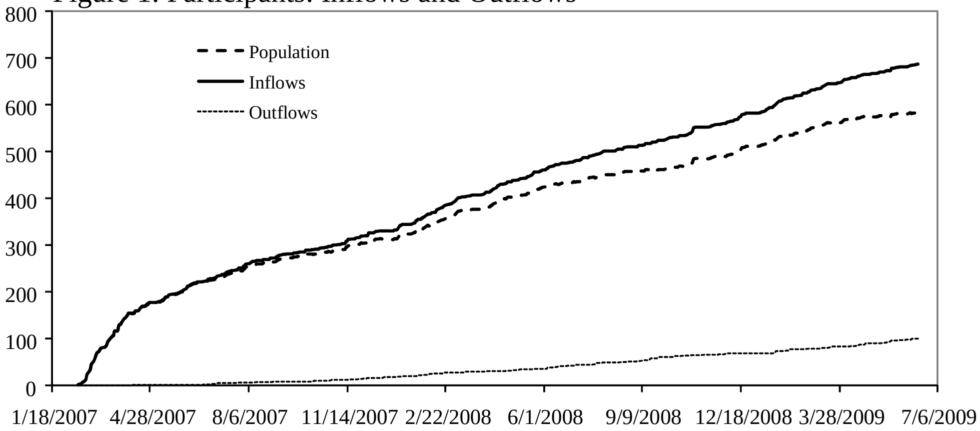
- A Participants file with pseudo and numerical identifiers of the contest participants.
- A Flows file with contributions and withdrawals of currency, and contributions and withdrawals of securities, for each participant and each day.
- An Orders file. These are conditional or firm.
- A Transactions file. This contains the hour, date and price of entry and exit, and quantities.
- A Portfolio Value file. This 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.

All files were cleaned of errors. They were also cleaned of fictive negative portfolio values resulting from the bad recording of the date of contributions.

1.4) Participants

Each participant (and their operations) who were registered at least once in one of the two contests are included in the data base. Participants remain in the base even when they cannot (or do not want to) take part in the contest any longer (having a portfolio value under 1000 Euros, the use of Warrants other than those emitted by Commerzbank etc.). This explains the considerable gap between traders who are in the base and those who are present in any given month in the contest. The “stock” of traders is generally four times larger than the number of active traders.

Figure 1: Participants: Inflows and Outflows



Note that the 2008 financial crisis did not affect the net inflow of traders. 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. In May 2009, gender was recorded for 656 of the 659 traders, and is distributed as follows:

Table 4: Gender of participants

Gender	Population	Percentage
Women	82	14.3
Men	574	85.7

The age distribution for the 561 traders with available information is shown in Table 5 (average age = 41).

Table 5: Age of participants

Age	**Age< 25**	**25≤age< 30**	**30≤age< 35**	**35≤age< 40**	**40≤age< 45**
Population	32	56	93	101	89
Percentage	5.7%	9.98%	16.57%	18%	15.8%
Age	**45≤age< 50**	**50≤age< 55**	**55≤age< 60**	**60≤age< 65**	**65≤age**
Number	71	44	31	24	20
Percentage	12.65%	7.84%	5.52%	4.27%	3.56%

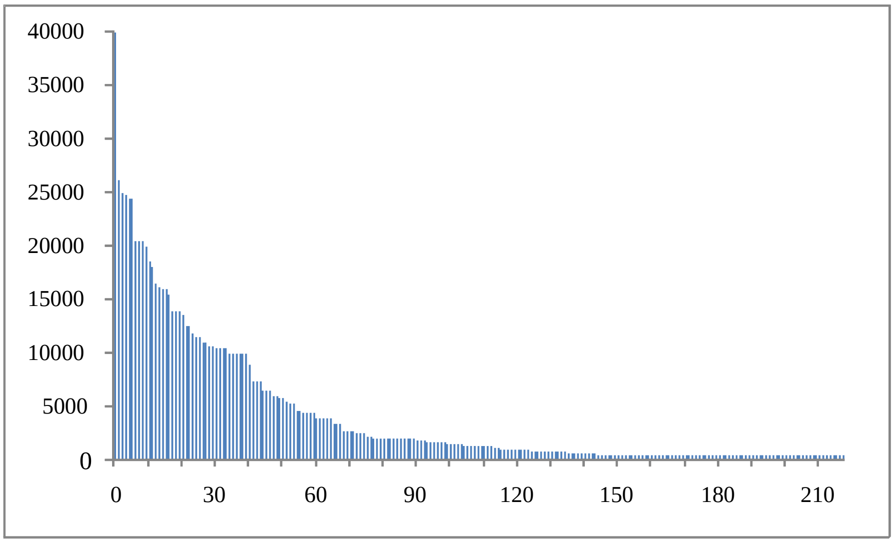
1.5) Contest Winners

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 6 shows that rewards double the portfolio value of winners on average.

Table 6: Number and value of rewards for winners:

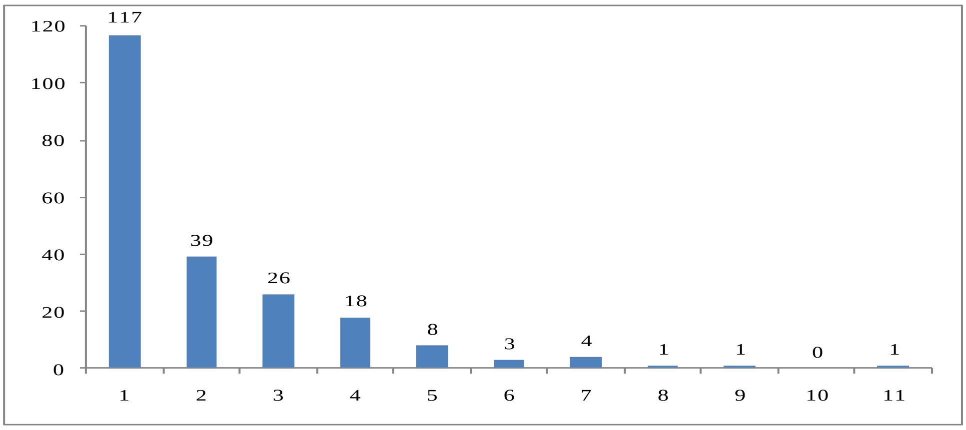
	Number of rewards	Portfolio value	Value of rewards	Reward ratio
Mean	2.11	2370.12	1746.50	0.99
Std deviation	1.66	2458.51	2211.61	1.42

Figure 2: Amount of rewards won (Y-Axis) by winners (X-Axis)



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



2) PERFORMANCES

2.1) The portfolio-value file

An extract of the basic portfolio-value file is reproduced below. We have added our calculation of the gains and performances per day per trader to the original file (See Section 2.2 for details of these calculations).

Table 7: Portfolio-value file

Participant	Date	SRD NET value	Stocks DEPOSIT	Cash	Portfolio value	Contribution (Assets)	Cash contributions	Total cont.	Gain	Day Return
176	02/27/2007	27.5	0	1000	1027.5	0	0	0	27.5	0.0275
176	02/28/2007	9.56	0	1952	1961.56	0	952	952	-17.94	-0.0119
176	03/01/2007	9.56	0	1929	1938.56	0	-23	-23	0	0.0000
176	03/02/2007	1.56	0	1929	1930.56	0	0	0	-8	-0.0041
176	03/05/2007	46.46	0	9929	9975.46	0	8000	8000	44.9	0.0076
176	03/06/2007	-133.41	3908.5	5979.59	9754.68	0	0	0	-220.78	-0.0221
176	03/07/2007	-146.85	3918	5979.59	9750.74	0	0	0	-3.94	-0.0004
176	03/08/2007	-208.95	4012	5979.59	9782.64	0	0	0	31.9	0.0033
176	03/09/2007	-229.65	0	9987.12	9757.47	0	0	0	-25.17	-0.0026
176	03/12/2007	-168.45	0	9987.12	9818.67	0	0	0	61.2	0.0063
176	03/13/2007	-194.55	0	9987.12	9792.57	0	0	0	-26.1	-0.0027
176	03/14/2007	-110.55	0	9987.12	9876.57	0	0	0	84	0.0086

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€ while the initial portfolio value was 3184€. Positions are taken by traders who enter the contest by investing more than the minimum required (1000€) and who have high portfolio values. Leverage is high in this data. We calculate this simply as the ratio of the transaction amount to portfolio value the day before the transaction. Absolute mean leverage is 1.79.

2.2) The calculation of performance

We now want to calculate the performance rate from the portfolio-value data file. These performances are net of transaction fees, which are recorded as negative contributions. This 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.

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. The time of day (opening/closing) when contributions and withdrawals are recorded will be important for this calculation.

Following standard portfolio-performance measurement, as in Christopherson, Cariño and Ferson (2009), we then apply the Dietz (1968) midpoint formula to the daily data: $r_t = \frac{v_t - v_{t-1} - (a_{C} + a_A)}{v_{t-1} + 0.5(a_{C} + a_A)}$, where *v* are dated portfolio values in *t* and *t-1*, and the α's are the net contributions of cash (c) or assets (a) (SRD and stocks).

This calculation yields the daily performance, and the cumulated daily values produce the adjusted values of traders' portfolios for each day. Performance over a period (week, month or year) is then simply the ratio of the adjusted closing portfolio value to the adjusted opening value.

2.3) The mean of idiosyncratic annualized performances

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.

Annualized output is calculated from the daily outputs cumulated over the duration of trading activity, $R = \prod_{t=1}^{t=T} \llbracket (1 + r_t \rrbracket) - 1$, which is then extrapolated, $R_A = (1 + R)^{\frac{252}{T}} - 1$.

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. Hence, if the market records positive returns while the trader's are negative, relative performances strictly below -1 can result. This can be interpreted as both an effective loss and an opportunity loss from not having strictly followed the SBF250 market.

Traders' results are much worse than that of the SBF 250, with amateurs having an average annual performance of -38%. The considerable variance in the results and the concentration of losses underline the usefulness of percentile indicators.

Table 8: 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
Min	12.00	300.00	600.00	-184
Max	853.00	50000.00	331500.00	654
Quantiles				
0.05	77.00	1000.00	1000.00	-105
0.1	125.30	1000.00	1000.00	-90
0.25	244.25	1000.00	1500.00	-71
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

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. However, Anderson (2006) considers annualized gains relative to wealth in a market period that was more favorable. Losses are therefore less drastic than those here, but the shape of the cumulative frequency distributions of results[4] is remarkably similar to ours.

[4] Anderson (2006), p. 35.

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. Note that over 5% lose more than 100% of their wealth, which is possible using the Dietz formula.

The empirical distribution of performance fits a Loglogistic (-2.6523; 2.1889; 8.2572) function (see Figure 4), with 90% of observations lying between -1.05 and 0.34 versus 86% for the theoretical distribution. We can also fit the data to a normal (-0.39; 0.60318) function. The distribution is leptokurtic with positive skewness (see Table 9). The Loglogistic distribution is also known as a Fisk distribution. Fisk (1961) showed that this distribution is the best fit for income distributions, with positive skewness and a “thin” distribution.

Figure 4: The empirical distribution and the Loglogistic distribution

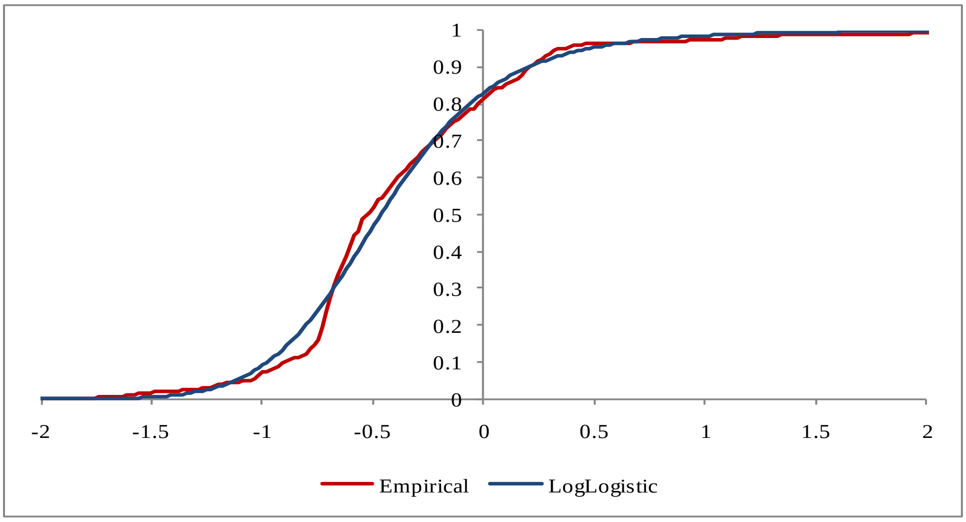


Table 9: The fit of the empirical distribution to classic distribution laws

Fit	LogLogistic	Pearson5	Logistic	InvGauss	ExtValue	Gamma	Normal	Weibull	Exponential
Chi-Squared Test									
	151.7161	189.4196	201.5331	213.9495	227.2744	233.0284	377.4069	410.9464	1120.9527
	0	0	0	0	0	0	0	0	0
Anderson-Darling Test									
	5.0386	10.4695	8.8639	12.3016	12.7125	13.5124	+Infinity	33.1339	130.3294
	N/A	N/A	<0.005	N/A	<0.01	N/A	<0.005	N/A	<0.01
Kolmogorov-Smirnov Test									
	0.0892	0.1215	0.1046	0.1246	0.1281	0.1274	0.1446	0.1948	0.3912
	N/A	N/A	<0.01	N/A	<0.01	N/A	<0.01	N/A	<0.01

Table 10: Empirical distribution statistics compared to those from Loglogistic and Normal distributions

Fit Function	Input	Loglogistic(-2.5329;2.0698;7.7062)	Normal(-0.37907;0.66262)
Distribution Statistics			
Minimum	-1.8396	-2.5329	-Infinity
Maximum	6.5427	+Infinity	+Infinity
Mean	-0.3791	-0.4046	-0.3791
Mode	-0.7328 (est)	-0.532	-0.3791
Median	-0.5197	-0.4631	-0.3791
Std. Deviation	0.6626	0.5185	0.6636
Skewness	4.1561	1.2843	0
Kurtosis	37.6833	8.8081	3

Performances including rewards

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%).

2.4) Performance statistics with random investment

We have above compared trader performance to that of the market. However, 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 11.

Table 11: Final portfolio distribution with random investment

Quantile	Market	Mean	25%	50%	75%	90%	95%	97.5%	99%	99.9%
Final Portfolio (Starting value=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 5: 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.

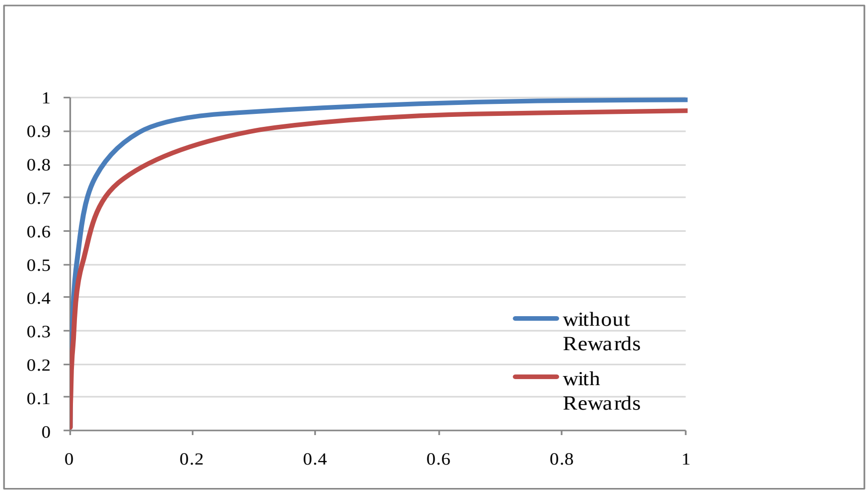
Figure 6: Performance paths for the top decile

The top 0.1 percentile of final portfolio experience good gains, but doing so means that the individual has to draw the 0.1 top percentile result every day. 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, 2000, 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.

Random performance 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.

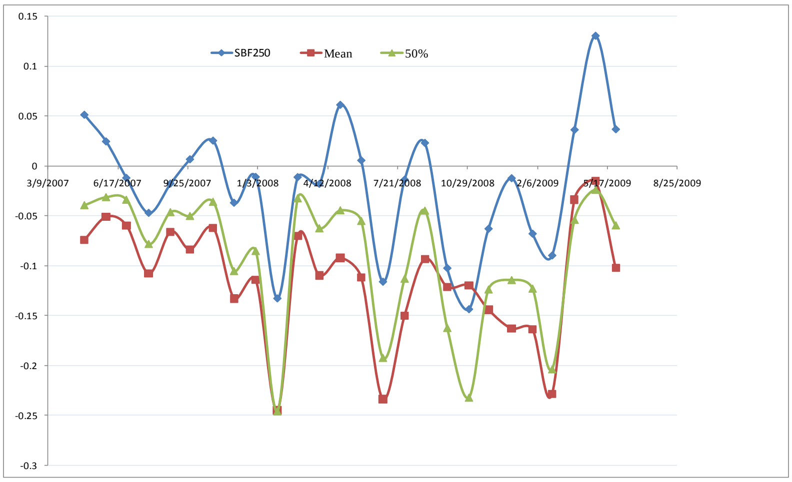
Figure 7: The distribution (Y-axis) of portfolio final values with/without rewards (X-axis)



2.5) Periodic analysis: monthly performance rates

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 8 shows that traders' monthly performances are always worse than that of the market: their losses are amplified, and their gains are smaller.

Figure 8: Monthly results of traders vs the Market without inactive traders



We restrict the analysis here to active traders, since there is clearly a link between the probability that traders beat the market in a given month (R>Rm) and the share of inactive traders. In a Bear market period, one good way to outperform the market is to do nothing and to hold the entire portfolio in cash. As in the famous analysis in Barber and Odean (2000), trading appears hazardous to one's wealth.

2.6) Performances by gender and age

In order to compare the performances of different types of traders, we look at the weekly performance of current traders by category. Overall performance by category is obtained by cumulating these weekly average performance figures. Total performance is then the performance of an abstract representative trader who each week earns the average of all traders. Performances by gender (Table 12) and age (Table 13), and in total (without extreme value biases) can be calculated.

For a start-up portfolio value of 100, the representative trader ends up with a portfolio value of only 7.15 at the end of the period. During this period, the market (SBF250) fell from 100 to 57.7. Average annualized performance is then -67.5% (traders) versus -20.9% (market); the relative annual performance is thus -46.6%.

Table 12 shows that women have better scores than men, although the difference is not significant (one-tailed t-test p-value=0.25). We thus differ from Barber and Odean 2001(2), where boys exhibit better performances than do girls.

Table 12: Performance by gender

Gender	Final Portfolio (Start up=100)	Average annualized perf.%
Women	9.34	-63.5
Men	6.89	-68
All traders	7.15	-67.5
SBF250	57.71	-20.9

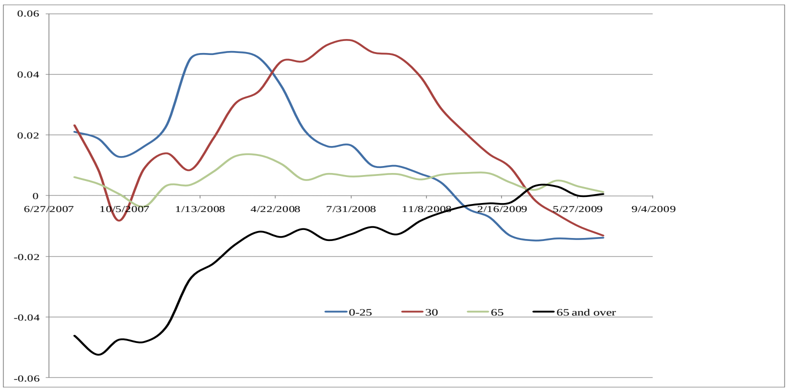
By age, the best performances are found amongst both younger (under 25) and older (over 65) traders. Note that there are relatively few traders in these age classes (see Table 4). Older traders perform significantly better than those aged 60-65 (one-tailed t-test p-value=0.028). Younger traders do better than those aged 25-30, but not significantly so (one-tailed t-test p-value=0.1).

Table 13: Performance by age

Age	Final Portfolio (Start up=100)	Average annualized perf.%
<25	14.27	-56.3
25-30	6.27	-69.2
30-35	6.02	-69.8
35-40	4.5	-73.3
40-45	5.48	-70.9
45-50	9.68	-63
50-55	4.38	-73.6
55-60	4.89	-72.3
60-65	4.98	-72.1
≥65	18.57	-51.2

Our intuition is that older people have less bad results simply because they are less active. We thus construct a relative activity index defined as the monthly difference between the share with nil performance (inactivity, entire portfolio in cash) in the total sample minus that in the age group under consideration. A positive (negative) index value refers to relative trading activity (inactivity).

Figure 9: The activity index by age



The relatively good performance of older traders obviously comes from their inactivity.

3) 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?

3.1) 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 autocorrelation distribution (for lags comprised between 1 and 12) is the same across deciles. We use the Kolmogorov-Smirnov (K-S) goodness-of-fit test (which is stricter than other tests such as the Chi-square).

In the Kolmogorov-Smirnov test we have the following hypotheses:

H_0: The Empirical Cumulative Distribution Function of the Autocorrelation coefficients by decile follows the ECDFA of the entire population.

H_1: The ECDFA of the decile does not follow the ECDFA of the entire population.

If H_0 holds then Table 14 shows the probabilities that the given statistic is drawn. That is, if this probability is below 5% we should reject the goodness-of-fit assumption and accept that there is a difference between the ECDFA of the given decile relative to the entire population.

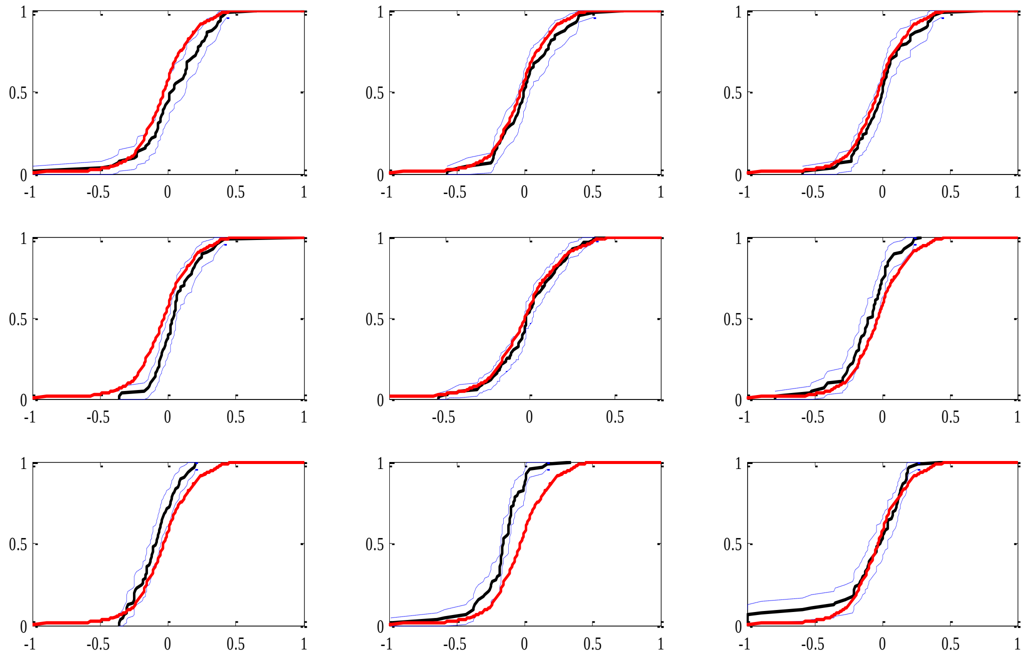
In Table 14, only lag 1 produces a KS test difference for 4 deciles. For the other deciles only the 9th is clearly always KS test different.

Table 14: ECDFA Kolmogorov-Smirnov statistics for deciles vs. population

KS stats	lag+1	lag+2	lag+3	lag+6	lag+9	lag+12
decile 1	2%	42%	65%	56%	39%	40%
decile 2	51%	18%	17%	13%	74%	82%
decile 3	44%	20%	18%	21%	0%	80%
decile 4	0%	6%	94%	63%	53%	74%
decile 5	36%	96%	67%	6%	19%	32%
decile 6	6%	70%	99%	22%	41%	14%
decile 7	3%	24%	28%	71%	1%	90%
decile 8	0%	0%	0%	0%	0%	3%
decile 9	55%	16%	64%	70%	68%	34%

Figure 10 shows the ECDFA (for lags +1) for the various deciles.

Figure 10: ECDFA lag +1 for each decile vs mean ECDFA and confidence interval



The black line in each plot is the ECDFA of each decile (deciles 5 and 6 are merged to make the figure less dense). 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 ECDF. Graphically, and in line with the previous results, 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 relatively more negative ECDFA 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 absence of persistence suggests the absence of skill among traders, even for those who have the best performances. Are the best traders just lucky?

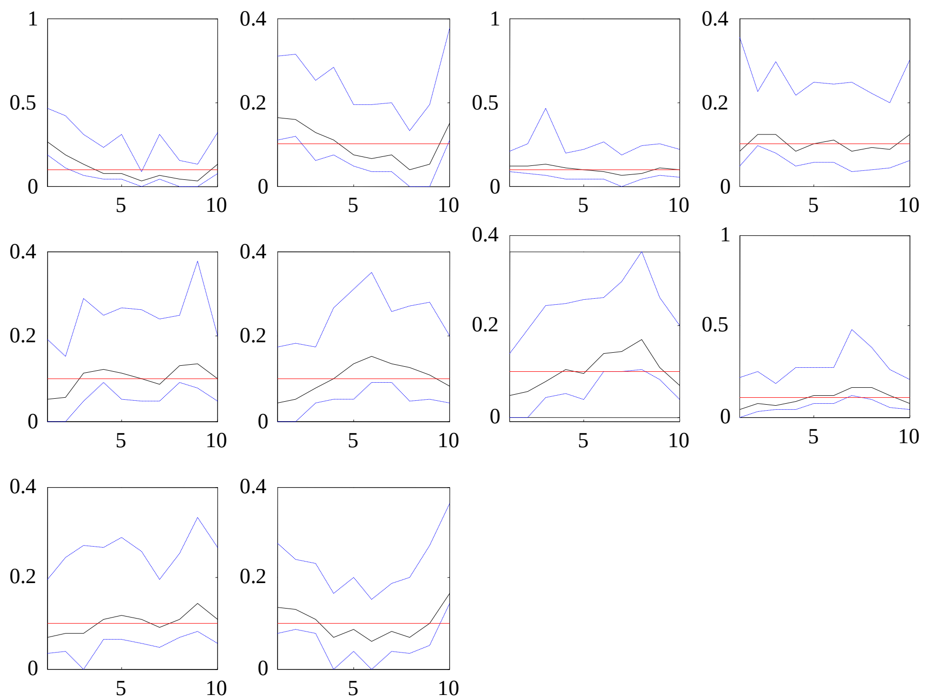
3.2) Transition analysis

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 *t*, for each decile d^k, the matrix of the frequency $\tilde{\pi}_{t+1}$ of the transitions of trader *i* to decile *j* the next month can be written as:

$$\tilde{\pi}_{t+1}(j\,|k) = prob(\{i \epsilon d_{t+1}^{j} | i \in d_t^k\})$$

In each month, each $\tilde{\pi}_{t+1}^{i}$ is considered as a random draw. Hence, we construct the statistics over the sample of the frequencies for each decile and obtain the matrix $\hat{\pi}$ of the mean transition frequency and the associated 90% confidence intervals.

Figure 11: The mean frequencies of transitions from deciles 1 to 10



The figure should be read as follows: for the tenth decile, the mean frequency of being in a given decile the next month is given by the black line. For instance this is 0.13 for being in the first decile, 0.10 in the ninth, and 0.17 in the last. If there were no persistence, the frequency would be 0.1 for all deciles (the red line), the equi-probability. The two blue dotted lines show the 90% confidence intervals. 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 sum up, in our data, a trader in the first decile has a 1/7 probability of being in the same decile the following month, whereas a lucky trader has only an analogous probability of 1/10.

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, with d_0 the initial decile and *T* the time horizon:

$$E\left(\frac{\{t \in \{1,\ldots,T\} \mid d^t = d^0\}}{T}\right)$$

In Table 15, 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.

Table 15: 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?

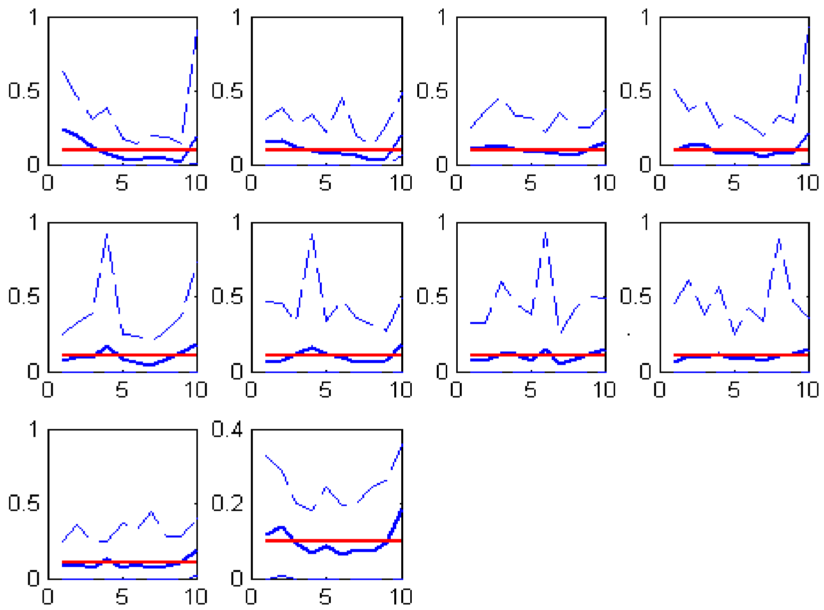
The previous analysis has provided only little support for skill-based explanations of trading success. This may be the case because there are so few skilled traders that the final decile analysis is not restrictive enough. We thus extract the star traders from the data and calculate their transition matrix over the 10 deciles[5] (defined for all competitors):

$$\tilde{\pi}_{t+1}(j \mid k) = prob(star \in d_j \text{ in period } t+1 \mid star \in d_k \text{ in period } t)$$

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.

[5] The 10 deciles being the same as in the previous calculus.

Figure 12: 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 13: Probability of staying in the top decile the next month

Table 16 : Long-term analysis with ergodic probabilities

deciles	hazard	population	≥1 prize	≥2 prizes	≥3 prizes
1	0.1	0.101	0.114	0.128	0.122
2	0.1	0.103	0.125	0.130	0.114
3	0.1	0.103	0.109	0.108	0.011
4	0.1	0.095	0.104	0.102	0.092
5	0.1	0.099	0.078	0.083	0.083
6	0.1	0.096	0.075	0.055	0.060
7	0.1	0.098	0.062	0.048	0.051
8	0.1	0.099	0.067	0.054	0.053
9	0.1	0.099	0.081	0.075	0.076
10	0.1	0.108	0.184	0.219	0.240

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 in terms of staying in the best decile.

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.

Their relative average annual performance varies from -38% to -60%, depending on the method used. 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. When we include the rewards offered by the contest, average performance becomes -13% a year. However, performances remain concentrated since only two deciles continue to beat the market. From an initial value of 100 the final value is 28 including rewards, but 95% of traders still lose in absolute.

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 chance. We thus cannot reject a “star effect” of staying in the best decile. However, the great majority of amateurs do seem to be e-pigeons. Online trading may just be costly entertainment, like casino gambling.

Our period covers the 2008 crisis and considerable losses may be the consequence of undiversified portfolios in a bullish market. This may explain the drastic losses observed relative to previous results on amateur traders (Anderson , 2006, Choi, Laibson, Metrick, 2002, Barber, Odean, 2001(1), Dom, Sengmueller, 2009, Mizrach and Weertz, 2009). More work is therefore warranted to better understand the causes of amateur traders' drastically bad performances.

REFERENCES

Alpert, M., and Raiffa, H., 1982, A progress report on the training of probability assessors, in: D. Kahneman, P. Slovic and A. Tversky, eds., Judgment Under Uncertainty: Heuristics and Biases, Cambridge University Press, Cambridge, pp. 294–305.

Anderson A., 2006, Is online trading gambling with peanuts? SIFR Research Report Series.

Barber, B., Lee, Y.T., Liu, Y.J., Odean, T., 2009, Just how much do individual investors lose by trading? Review of Financial Studies 22, 609–632.

Barber, B., Odean, T., 2000, Trading is Hazardous to your Wealth, *The Journal of Finance*, LV (2), 773-806.

Barber, B., Odean, T.,2001(1), The Internet and the investor. *Journal of Economic Perspectives* 15, 41–54.

Barber, B., Odean, T., 2001(2), Boys Will be Boys: Gender, Overconfidence, and Common Stock Investment, *Quarterly Journal of Economics*, 116 (1), 261-292.

Barber, B., Odean, T., 2002, Online investors: do the slow die first? *Review of Financial Studies* 15, 455–487.

Blanchard,O., 2000, E-Pigeons, *Libération*, Tribune, 20 mars.

Choi, J., Laibson, D., Metrick, A., 2002, How does the Internet affect trading? Evidence from investor behavior in 401(k) plans, *Journal of Financial Economics* 64, 397–421.

Christopherson, J., Cariño, D., Ferson, W., 2009, Portfolio Performance Measurement and Benchmarking, McGraw-Hill, Finance and Investing

Cubitt, R., Sugden, R., 2001, On Money Pumps, *Games and Economic Behavior*, 37 (1), 121-160.

Dietz, P., 1968, Components of a Measurement Model: Rate of Return, Risk and Timing, *The Journal of Finance*, 23 (2), 267-275.

Dom, D., Sengmueller, P., 2009, Trading as Entertainment? *Management Science*, 55 (4), 591-603.

Fisk P., (1961), The Graduation of Income Distributions, *Econometrica*, 29 (2), 171-185.

Jegadeesh, N., Titman, S., (1993), Returns to buying winners and selling losers: implications for stock market efficiency, *Journal of Finance* 48, 65−91.

Mizrach, B., Weertz, S., 2009, Experts online: An analysis of trading activity in a public internet chatroom, *Journal of Economic Behavior and Organization* 70, 266-281.

Odean, T., 1999, Do Investors Trade too much?, *American Economic Review*, 89, 1279-1298.

Shefrin, H., Statman, M., 1985, The disposition to sell winners too early and ride losers too long: theory and evidence, *Journal of Finance*, s40, 281-304.