Quantum Particle Swarm Optimization for Short-Team Portfolios

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This study examines proprietary transaction data for 2,726 accounts and 256,674 roundtrip transactions from November 2004 to January 2015. This study finds that the average individual investor in this sample earns $23.87 per trade. The results show that individual investors exhibit the disposition effect in their trades. Additionally, the study uses the Quantum Particle Swarm Optimization (QPSO) to form optimal short-term portfolios using individual investors trading data as the training points for the QPSO algorithm.

The results show that QPSO yields better in sample optimized portfolios with respects to measures of risk and return than do optimized portfolios using Markowitz or Genetic Algorithm techniques (GA). The results also show that using individual investors trading data as the training points for the QPSO algorithm, yield more superior out of sample optimized portfolios than using historical data as the training points for QPSO. The optimization is carried out by minimizing these three risk measures Variance, Value at Risk (VaR) and the Conditional Value at Risk (CVaR) for the portfolios.

INTRODUCTION

Nofsinger [2001], the field of finance has evolved over the past few decades based on the assumption that people make rational decision making. Shiller [2002] provided theoretical and empirical evidence to support the fact that Capital Asset Pricing Model (CAPM), Efficient Market Hypothesis (EMH), and other traditional financial theories did an excellent job in predicting and explaining certain events. The Modern Portfolio Theory (MPT), the CAPM and the Arbitrage Pricing Theory (APT) describe the rational expectations theory.

However , Fama and French, [1993, 1996] have shown that the stock market is not understood using these theories because of various individual trading behavior [Banerjee, 2011] . Daniel Kahneman and Amos Tversky [1970] gave rise to the Behavioral Finance paradigm which argued that various financial phenomena would be better understood. Per Sewell [2007] individual psychology affects the behavior of individual investors and capital markets.

The performance of individual investors has been well documented in the literature. Jordan and Diltz [2003] examine the profitability of individual investors and find that some individual equity investors (hereafter individual investors) can earn small profits on their trades. However, twice as many individual investors lose money as for making money. Furthermore, only one in five individual investors is more than marginally profitable. One possible explanation for these results is that some individual investors are overconfident. Previous studies of individual investors have found that individual investors trade excessively and that this causes their performance to deteriorate (Barber and Odean [2000]; Barber, Lee, and Odean [2003]). [Barberis and Thaler, 2003] support the ideas that cognitive psychology affects individual investors decision making process.

Tversky and Kahneman [1976], developed the Prospect Theory that showed irregularity of human behavior in the way they assess risk. [Chen et al., 2007, and Pompian, 2006] contend that behavioral biases are similar to systematic errors. Chandra (2008) reports that there are many behavioral factors like Greed and Fear, Cognitive Dissonance, Heuristics, Mental Accounting, and Anchoring that affects the process of decision making.

The study examines transaction data of 2,726 accounts of individual investors. The proprietary data set provides detailed transaction information for each investor: When each transaction starts and ends, as well as its quantity, opening price, and closing price. The individual investors in the sample are a representation of individual investors to the general public. In other words, these individual investors are not professionals, and they are not sophisticated in the art of finance. Grinblatt and Keloharju [2001], Dorn and Huberman [2005] report that individual investors don't diversify their portfolios and that is driven by behavioral biases such as familiarity bias or overconfidence bias.

Markowitz [1952] used mathematical methods for portfolio optimization based on a simple trade-off between risk (variance) and return (mean) given the correlation between the assets in the portfolio. The definition of variance reflects symmetry as one size fits all which does not take into account the behavior of stock returns. The mean variance frame work doesn't accurately reflect risk perception of individual investors. Zadeh [1965] explained how to integrate investors subjective opinions into portfolio selection through using the Fuzzy Set Theory. It permits the continuous assessment of the membership of elements in a set; this is described with the aid of a membership function of a valued in the real unit interval [0, 1]. Chen [2009] and Zhang et al. [2009] examined the mean-variance utility possibility in portfolio selection

The use of mathematics has become very extensive in the financial world, most of the mathematical models concentrate on the market data rather than the behavior of the individual actors from which the data has been generated. Heuristic algorithms such as genetic algorithm (GA) can solve complex nonlinear programming problems and find an optimal solution Chang et al. [2000]. Particle swarm optimization is a heuristic global optimization method developped by Kennedy and Eberhart [1995]. This global optimization algorithm can be used to work out the complex optimist problems Zheng Jianchao [2004]. PSO is not a global convergence- guaranteed optimization algorithm, as Van den Bergh has demonstrated [2001]. Therefore, Sun et al. [2004] proposed a global convergence-guaranteed search technique, Quantum Particle Swarm Optimization (QPSO) whose performance is superior to the PSO. The QPSO is suggested by combining the classical PSO philosophy and quantum mechanics to improve the performance of PSO.

In this paper, we will use a QPSO based portfolio volatility to select the best portfolio set. The QPSO method is highly efficient and effective in providing near optimal solutions within a few minutes. The following questions motivate this study: Do individual investors earn profits? How significant are these benefits? Do individual investors have certain behavioral biases? Is using individual investors trading data as training points for the QPSO will yield more superior out of sample optimal portfolio selections than using the common historical data?

The results are summarized as follows. The study finds that the average individual investor in this sample earns $23.87 per trade, which is significantly different from zero. The cross-sectional sorts on performance reveal considerable variation in performance. The top performers earn $46,421 per trade while the worst performers earn -$38,904 per trade. Both are significantly different from zero. Overall, the results reveal that approximately 50 percent of the investors in this sample can earn a real profit per trade. However, this study shows that certain behavioral biases (Disposition effect) influence some investors and that may explain why some earn profits, and some incur losses, but on average they gain more than they lose. Finally, this study shows that using individual investors' trading data as training points for the QPSO algorithm to form out of sample short term optimal portfolios will yield more excellent optimal portfolio selections than using the common historical data to form out of sample optimal portfolio selections.

RELATED LITERATURE

Odean [1999] on the performance of individual investors "As they gain profits, overconfident individual investors overweight the strength of their private information, which leads to excessive trading and lowers performance." Gervais and Odean [2001] refered to that phenomena as overconfidence. Individual investors hold under-diversified portfolios (Goetzmann and Kumar [2004]) and to take highly idiosyncratic risks (Calvet, Campbell, and Sodini [2007]), and they gamble in the stock market (Kumar [2009]).

Studies, such as Brock, Lakonishok, and LeBaron [1992] and George and Hwang [2004], document the significant power of technical characteristics in explaining security returns. The disposition effect is a tendency to sell winners quickly and hold on to losers, as described by Shefrin and Statman [1985]. Individual investors provide a powerful test of the disposition effect because they tend to have short holding periods. As Farrell [1999] states, "What is a day trader's recipe for disaster? Cutting your winning trades and riding your losses right into the ground."

To this end, this study collects return and risk expectations in a repeated panel survey of self-directed individual investors. These investors are queried about their numerical and qualitative expectations and their risk tolerance. The study also observes the volume, timing, and direction of all trades and can calculate the portfolio holdings of individual investors and their profits and losses

DATA

The data is obtained from an online advisory service for individual investors. The sample consists of 2,726 accounts and 256,674 roundtrip transactions from November 2004 to January 2015. The data include the individual investor's name, a unique account identification number, when the position was opened and closed, the opening and closing prices, and many other identifiers. We used a questionnaire to capture opinions and attitude, and we used Taylor et al. [2006] to design and quantify the questionnaire results.

PROFIT/LOSS AND CROSS-SECTIONAL VARIATION IN PERFORMANCE

Table 1 presents summary statistics for all 2,726 account holders. For each account, the study estimates *Trade size*, *Trades per day*, *Age*, *Hold time in hours*, and the *total Number of Trades*. *Trade size* is defined as the number of contracts per position, times the open price paid. *Trades per day* are defined as the total number of trades executed by an account holder, divided by the age measured in days. *Age* is defined as the length an account is held open measured in calendar days. *Hold time in hours* is defined as the duration in hours a position is held open before it is closed. *Total Number of Trades* is defined as the number of trades executed by an account holder over the entire length of the account. Table 1 shows that the mean *Trade Size* in USD is 27,085, mean *Trades per day* is 0.46, the average age is 205 days, mean *Hold time* is 206 hours, and the mean for *Total Number of Trades* is 94 trades.

TABLE 1
PRESENTS SUMMARY STATISTICS FOR ALL 2,726 ACCOUNT HOLDERS

ITEM	*MEAN*	*25th PCT.*	*MEDIAN*	*75th PCT.*	*OBS*
Trade size ($USD)	27,085	3,694	9,184	20,580	256,739
Trades per day	0.46	0.08	0.24	0.78	2,726
Age(days)	205	21	99	253	2,726
Holdtime(hours)	206	6	30	144	256,739
Number of trades	94	2	13	54	2,726

Table 2 presents the demographic characteristics of individual equity investors. Table 2 shows that 7% of investors in the sample is between the ages of 18-25, 39% are between the age of 26-40, and 54% are age 41 and above. It also shows that 45% of investors in the sample hold associate's degrees or lower, while 55% of the sample hold bachelor's degrees or higher.

TABLE 2
PRESENTS THE DEMOGRAPHIC CHARACTERISTICS OF INDIVIDUAL EQUITY INVESTORS

DEMOGRAPHIC CHARACTERISTICS	ONLINE INVESTORS	FREQUENCY COUNT	PERCENT OF TOTAL FREQUENCY
Age		N=178	
	18-25	13	7%
	26-35	46	26%
	36-40	23	13%
	41-50	42	24%
	>50	54	30%
Education		N=178	
	Associate's degree	38	21%
	Bachelor's degree	62	35%
	High school	43	24%
	Master's or higher	35	20%
Trading Experience		N=178	
	Less than one year	82	46%
	One to two years	27	15%
	Two years or more	69	39%
Risk Level		N=178	
	I am risk-averse	46	26%
	I am a risk seeker	47	26%
	I am neutral	85	48%

Table 3 describes the per trade profit/loss for the sample. Table 3 Panel A shows that individual investors in this sample can earn a mean profit per trade of \$23.87, which is significantly different from zero (t-statistic=2.40). Furthermore, there is considerable cross-sectional variation in performance. The bottom 25th percentile earns a negative -\$141.00 per trade while the top 75th percentile earns \$180.00 per trade.

The study next examines the cross-sectional performance of these investors. The study obtains the mean profit and loss for each account holder, ranks all accounts into deciles based on their mean profit and loss, and places them in deciles with D_1 containing the top performing account holders and D_{10} containing the worst performers. Furthermore, the study calculates the statistical significance of the profits and losses as being reliably different from zero. Table 3 Panel B presents the results for the various deciles of performances.

The most notable observation of Table 3 is that there is significant cross-sectional variability in performance. D_1, which contains the top performers, earns a mean profit per trade of $46,421, and this is reliably different from zero (t-statistic=6.02). This amount is considerably larger than the next decile (D_2), which earns a mean profit per trade of $17,446, which is also statistically significant (t-statistic=6.83). Another notable observation is that the worst performing investors lose significant amounts of money per trade. The worst performers, in D_{10}, lose $-38,904 per trade, and this is significant (t-statistic=-5.15). The next group, in D_9, loses considerably less than the group in D_{10}, with a mean loss of $ -10,867 per trade that is also reliably different from zero (t-statistic-11.53). Overall, the results of the cross-sectional performance reveal that approximately 50 percent of the investors in this sample can earn positive and statistically significant profits.

TABLE 3
FULL SAMPLE RESULTS OF PROFIT/LOSS PER TRADE

PANEL A

Profit and Loss Per Trade for 2,726 Account Holders

ITEM	MEAN	25th PERCENTILE	MEDIAN	75th PERCENTILE	OBS.
Profit/Loss Per Trade	23.87	-141.00	4.00	180.00	256,739
t-statistic	(2.40) *				

PANEL B
DISTRIBUTION OF PROFIT AND LOSS FOR INDIVIDUAL INVESTORS ACROSS 10 DECILES

Item	Mean	25th Pct.	Median	75th Pct.	Obs.
D_1	$46,421.00 (6.02) *	$3,470.50	$10,314.00	$35,910.00	272.00
D_2	$17,446.00 (6.83) *	$944.00	$4,878.00	$17,086.00	273.00
D_3	$11,282.00 (6.39) *	$695.00	$3,395.00	$10,156.00	273.00
D_7	$(3,791.00) (-8.31) *	$(3,983.00)	$(1,437.00)	$(339.00)	272.00
D_8	$(7,512.00) (-8.29) *	(8,308.00)	$(2,796.00)	$(630.00)	273.00
D_9	$(10,867.00) (-11.53) *	$(13,583.00)	$(4,681.00)	$(1,440.00)	273.00
D_{10}	$(38,904.80) (-8.3) *	$(43,785.00)	$(15,542.00)	$(6,035.00)	272.00

BEHAVIORAL BIASES AND PERFORMANCE VARIABILITY

The study examines the "*Disposition Effect" by investigating* the length of time individual investors will hold unprofitable trades to the term of time they will hold profitable trades. Table 4 Panel A considers whether there is a mean difference between holding times for profitable trades and unprofitable trades; it shows that there is a mean difference of 1,242 minutes between unprofitable and cost-effective trades. Table 4 Panel B further investigates whether the average difference found in panel A is significant. Table 4 Panel B shows that there is a statistically significant time difference between the two types of trades.

TABLE 4
DIFFERENCE IN MEAN FOR TIME HELD VARIABLE

PANEL A	N	MEAN	STD DEV	STD ERR	MINIMUM	MAXIMUM
Profitable Trades	972	439.4	1363.5	43.7339	0.00588	19086.9
Non-Profitable Trades	944	-803.0	2936.1	95.5608	-47417.9	0
Diff (1-2)		1242.3	2278.2	104.1		

PANEL B

METHOD	VARIANCES	DF	T-VALUE	PR > |T|
Pooled	Equal	1914	11.93	<.0001
Satterthwaite Equality of Variances	Unequal	1323	11.82	<.0001

Next, in Table 5 the study estimates two sets of t-statistics by the individual investor. The first round of t-tests comprises the time differences between profitable trades and unprofitable trades by an individual investor using the procedure of Dixon and Massey [1969]. The study hypothesizes that the disposition effect will cause more investors to have a statistically significant negative time difference than a statistically significant positive time difference. Table 5 shows that the difference in holding time between profitable trades and unprofitable trades is negative and significant, as demonstrated by the corresponding t-statistics of individual investors. Additionally, the frequent occurrence of negative time differences between profitable trades and unprofitable trades is high, which means that the disposition effect characterizes individual investors. The second set of t-statistics compares the difference in holding times for each investor's trades with the rest of the sample, and the t-statistics are still negative and significant for most of the individual investors. The above results show that individual investors exhibit the disposition effect.

TABLE 5
PRESENTS THE ANALYSIS OF THE DISPOSITION EFFECT.

		Profitable Trades			Unprofitable Trades				t-statistic	
Investor ID	No of Days Traded	Total No	Average Time Held	Variance of Time Held	Total No	Average Time Held	Variance of Time Held	Diff in Time Held	Individual Trader	Within Population
42999746	18.55	63.45	82.125	6,589.63	94.5	18.744	2,875.56	63.381	5.395	30.695
43000031	37.1	368.55	29.445	2,758.04	156	85.956	11,528.76	-56.511	–9.89	–36.88
43000184	5.3	8.1	69.945	970.39	6	106.8	20,667.50	-36.855	–0.89	–19.00
43001121	5.3	67.5	34.395	857.24	52.5	45.504	6,370.45	-11.109	–3.22	–11.92
43012446	5.3	132.3	47.955	2,980.19	45	69.06	8,253.62	-21.105	–4.72	–19.57
43024221	10.6	70.2	31.59	5,223.18	60	27.528	4,211.44	4.062	–0.19	–0.44
43024228	10.6	268.65	43.59	2,331.81	138	77.796	7,444.60	-34.206	–8.39	–20.04
43028565	5.3	6.75	162.195	9,528.65	6	31.8	7,414.40	130.395	3.58	40.69
43029133	5.3	52.65	54.765	3,203.61	73.5	99.18	2,908.47	-44.415	–7.36	–25.79
43029159	26.5	1360.8	34.845	3,019.94	475.5	44.124	7,316.47	-9.279	–5.26	–8.07
43029453	5.3	79.65	14.73	224.43	61.5	10.956	375.02	3.774	0.33	0.56
43029701	5.3	210.6	35.28	2,400.51	79.5	99.192	17,122.50	-63.912	–6.89	–24.56
43034379	5.3	6.75	5.88	13.83	6	16.8	18.20	-10.92	–5.64	–4.52
43047377	2.65	10.8	54	4,267.14	25.5	47.784	7,208.64	6.216	–0.19	–6.71
43047388	5.3	109.35	22.26	1,080.76	100.5	30.456	1,599.22	-8.196	–3.13	–7.76
43048588	7.95	56.7	106.035	7,164.00	39	88.776	5,975.30	17.259	–0.29	–4.47
43048653	29.15	564.3	53.58	2,118.59	474	62.16	7,038.72	-8.58	–5.63	–7.65
43049255	15.9	314.55	62.865	4,497.08	231	84.996	10,405.14	-22.131	–6.62	–13.19
43049856	7.95	14.85	96.09	8,386.69	7.5	131.868	218.86	-35.778	–2.91	–24.55
43049899	5.3	40.5	15.465	149.41	66	19.02	913.96	-3.555	–1.83	–2.93

SHORT-TERM PORTFOLIO OPTIMIZATION

The main objective is to optimize the portfolio set based on appropriate threshold selection. The PSO is a stochastic optimization technique introduced by [Kennedy and Eberhart, 1995]. PSO is a metaheuristic technique and do not guarantee an optimal solution is ever found. In QPSO the behavoir of the particles depends on the probability of the particle velocity and speed which in turn depends on the Probability Density Function (PDF) the form of which depends on the potential field the particle lies in.

METHODOLOGY

METHODOLOGY FOR IN SAMPLE SHORT TERM PORTFOLIO SELECTION

Given the behavioral biases discussed earlier in the paper, in PSO with M individuals, a potential solution to a problem is represented as a particle flying in D-dimensional search space, with the position vector $X_i = (x_{i1}, x_{i2}, \dots, x)$. and velocity $V_i = (v_{i1}, v_{i2}, \dots, v_{id})$. Each particle records its best previous position (the position giving the best fitness value) as $p_{besti} = (pbest_{i1}, pbest_{i2}, \dots, pbest_{id})$ which is called personal best position. At each iteration, each particle competes with the others in the neighborhood or in the whole population for the best particle (with best fitness value among neighborhood or the population) with best position $gbest_i = (gbest_{i1}, gbest_{i2}, \dots, gbest_{id})$) which is called global best position, and then makes stochastic adjustment according to the following evolution equations.

$$V_{id} = w, v_{id} + c_1, rand_1().(pbest_{id} - X_{id}) + c_{2,} rand_2().(gbest_{id} - X_{id}) \tag{1}$$

$$X_{id} = x_{id} + v_{id} \tag{2}$$

For $i = 1, 2 \dots., M;\ d = 1 \dots., D.$ In equation x, c_1 and c_2 are positive constant; $rand_1()$and $rand_2()$are two random functions generating uniformly distributed random numbers within [0, 1]. Parameter w is the inertia weight introduced to accelerate the convergence speed of the PSO. At each iteration, the value of Vd_{id} is restricted in $[-V_{max}, [V_{max}]$. In the QPSO the particles move based on the following iterative equations

$$x_{id}(t+1) = \left[g_{id} \pm \beta \left\{mbest_d - x_{id}(t)\right| \ln\left(\frac{1}{u}\right)\right\}\right] \tag{3}$$

Where
$g_{id} = \emptyset.pbest_{id} + (1 - \emptyset)gbest_d$,
And
$mbest_d = \sum_{i=1}^{M} pbest_{id/}M$

$mbest$ (mean best position or mainstream thought point) is defined as the mean value of all particles' the best position, $\emptyset$ and u are random number distributed uniformly on [0,1] respectively and m, is the number of particles. $L = \beta\left||mbest_d| - |x_{id}(t)|\right|.1n(1Iu)$ can be viewed as the strength of creativity or imagination because it characterizes the knowledge seeking scope of the particle, and therefore the larger the value L, the more likely the particle find out new knowledge. The parameter, β, called contraction-expansion coefficient, is the only parameter in QPSO algorithm. From the results of stochastic simulations, QPSO has relatively better performance by varying the value of β from 1.0 at the beginning of the search to 0.5 at the end of the search to balance the exploration and exploitation [Sun et al., 2005]

We define risk as the fluctuations of return, so first to calculate the rate of return we use the following equation

$$max\, Z_1 = \sum_{i=1}^{n} x_i\, r_i \tag{4}$$

Where, x_i is the proportion invested in various assets when the best trade-off is found and r_i is the expected rate of return of assets. Since we defined risk as fluctuation of return then minimizing of the significance of variance, as an objective, to decrease the fluctuation of portfolio return we use the following equation

$$min\ Z_2 = \sum_{i=1}^{n} x_i^2\, \partial_i^2 + \sum_{i=1}^{n}\sum_{j=1}^{n} x_i x_j\ \partial_{ij} \tag{5}$$

Where δ_i^2 and δ_{ij} are the variance and covariance of excess returns, respectively. Then we define the next objective. Beta β is the indicator of systematic risk. The objective of the minimum systematic level of risk can also be defined using the following equation

$$min\ Z_3 = \sum_{i=1}^{n} x_i\, \beta_i \tag{6}$$

Then we defined the objective for selecting a portfolio with a positive distribution of return skewness, because individual investors are looking to select a stock with positive return distribution. We used the following equation

$$max\ Z_4 = \sum_{i=1}^{n} S_{iii}^3\, x_i^3 + 3\ \sum_{i=1}^{n} \langle \sum_{j=i}^{n} x_i^2\ \ X_j S_{iij} + \sum_{j=1}^{j-1} X_j\, X_j^2 S_{ijj} \rangle\ i \neq j \tag{7}$$

Where, S_{iii}^3 is the skewness and, S_{iij} and S_{ijj} are co-skewness of the excess returns. Individual investors are also looking for liquidity. To calculate the risk of company liquidity, we can use the ratio of the number of days in which the company's stock was dealt over the number of the days in which the company was active in the market. Therefore, the objective of maximizing portfolio liquidity can be stated as:

$$max\ Z_5 = \sum_{i=1}^{n} x_i\, e_i \tag{8}$$

Where, e_i is the liquidity of assets. Individual investors aim to invest in a way to achieve the maximum level of excess returns (more return at the expense of risk they accept). We use the following equation

$$max\ Z_6 = \sum_{i=1}^{n} x_i\, S_i \tag{9}$$

Where, S_i is the liquidity of the assets. To determine the level of investment in a portfolio with QPSO, we must determine an encoding of particle's position and a fitness function. A particle's position encoding is most important factor in QPSO that is affected by the size of the search space. The particle's position of the current problem has 50 genes. The decimal of each gene indicates a collection of answers related to the amount of investment in each company. The figure below shows the particle's position encoding.

Index:	**1**	**2**	**....**	**60**
The amount of investment:	0.15	0.28	....	0.91

Another important factor is a fitness function. The complete and appropriate fitness function is showed in equation

$$F(x) = \frac{n_1 - Z_1}{h_1} + \frac{Z_2 - P_2}{h_2} + \frac{Z_3 - P_3}{h_3} + \frac{n_4 - Z_4}{h_4} + \frac{n_5 - Z_5}{h_5} + \frac{n_6 - Z_6}{h_6} \tag{10}$$

Where Z_i, $n_{i,}(p_i)$and h_i are respectively the objective functions. Reviewing and analyzing individual investors transactions, we concluded that the maximum level of investment in each stock was 0.91. The fitness amounts for the objectives such as maximizing the portfolio return (n_1), minimizing the non-systematic risk (p_2), maximizing the stock return skewness (n_4), maximizing the level of portfolio liquidity (n_5) and maximizing the Sharp ratio (n_6) in portfolio were measured as [8.951, 10.125, 0.776, 0.115 and 0.9], respectively through solving the single objective programming problems. Since the normal beta in a market is 1.0 and the stocks whose beta is more than 1.0 are risky stocks and that the distribution of the return of such stocks is enormous; also, considering that those stocks whose beta is less than 1.0 are safe stocks and the distribution of their return is limited, accordingly we considered 1.0 as the fitness amount of systematic risk objective (p_3).

Using the methodology developed by Saeed et al [2013] we ran the algorithms that were coded using JBuilder. Also, the initial populations of all algorithms consist of random individuals. Moreover, each experiment (for each algorithm) was repeated 40 times with different random seeds. All algorithms run in similar conditions. Then we compared the results of portfolio formed using QPSO with portfolios formed using Markowitz techniques. To compare the results, we use the return of the in-sample portfolio within the 72 months' period ending in June 2014. Table 6 shows that the model which has been solved using QPSO has produced 71 stocks in the portfolio which is more than both the GA model and the Markowitz model of (41 and 25 respectively) with less amount of non- systematic risk. The model solved by QPSO results has returns of (10.9) compared to Markowitz model (9.05). The QPSO Trynor score of (3.65) and the Markowitz model Trynor score of (3.81), which indicates less risk using the QPSO model which is also supprted by higher sharpe ratio for the QPSO of (0.39) compared to Markowitz model sharpe ratio of (0.13)

TABLE 6
EX-POST PERFORMANCE OF PORTFOLIOS

MODEL	MARKOWITZITZ MODEL	GA MODEL	QPSO MODEL
Average Rate of Return	9.05	12.14	10.9
Standard Deviation	40.53	32.12	18.55
Treynor Ratio	3.81	3.5	3.65
Sharpe Ratio	0.13	0.268	0.39
Number of Stocks	25	41	72

METHODOLOGY FOR OUT OF SAMPLE SHORT TERM PORTFOLIO SELECTION

Given the behavioral biases discussed earlier in the paper, an individual investor wants to select an optimal portfolio among stocks over a given moment horizon. This investor can select different positions among various stocks because the share prices are unknown; then, he/she is confronted with random price movements. Investors look for portfolios with a low probability of losses, which is a function of the stocks selected and their random market prices. The study uses the method employed by Allen and Powell [2009] and uses the three risk measures used in their methodology for selecting the optimal portfolio in a risk-return framework; these are the Variance, Value at Risk (VaR), and Conditional Value at Risk (CVaR).

The Variance of losses ($v(\Lambda)$) per the definition is:

$$\mathrm{K}(\Lambda) = Variance(\Lambda) = v(\Lambda) = \mathrm{E}(\Lambda - \mathrm{E}(\Lambda))^T - (\Lambda - \mathrm{E}(\Lambda)) \tag{11}$$

To choose the optimal portfolio with a minimal level of Variance, this nonlinear model is used in this paper

$$Min_x v(\Lambda) = v^{-2}\, X^T \left[\frac{1}{N}\sum_{j=1}^{N}(y_j-\bar{y})(y_j-\bar{y})\right] X \tag{12}$$

$$v^{-2}(v^{-}X^T\bar{y}) \le \rho$$

$$X^T\rho = v$$

$$X \ge 0$$

The VaR of losses $(\Lambda)_\beta\xi)$ is defined in the literature as:

$$\mathrm{K}(\Lambda) = VaR(\Lambda) = \xi_\beta(\Lambda) \tag{13}$$

VaR could be defined as "*a loss that will not be exceeded at some specified confidence level*" [Gaivoronski et al., 2005]. In the other word, "*the 100a% h-day VaR is that number x such that the probability of losing x, or more, over the next h days' equals 100a%*" [Alexander, 2001]. But formally $(\Lambda)_\beta\xi)\beta$is defined as βpercentile of loss distribution function [Fusai et al., 2001], then $(\Lambda)_\beta\xi)$is a smallest value such that probability that loss does not exceed to this value is bigger or equals to β [Kluppelberg et at., 1998].

$$\xi_\beta\,(\Lambda) = Min\;[\xi \in R{:}\, P\{\Lambda \in \le \xi\} \ge \beta] \tag{14}$$

Concerning the optimization of VaR, per the definition, the VaR of losses is the βN^{th}minimum of all loss scenarios in the sample PDF

$$\xi_\beta\,(\Lambda) = Min^{[\beta N]}\left[v^{-1}(\,v^{-}X^T y_{1)}, v^{-1}(\,v^{-}X^T y_{2)}, \dots\dots, v^{-1}(\,v^{-}X^T y_{n)})\right] \tag{15}$$

Where βN is the smallest integer non-smaller thanβN. Then, to find the optimal portfolio with the minimum level of losses VaR, we should minimize the βN^{th} minimum of all scenarios in the sample PDF of loss:

$$Min_x\xi_\beta\,(\Lambda) = Min^{[\beta N]}\left[v^{-1}(\,v^{-}X^T y_{1)}, v^{-1}(\,v^{-}X^T y_{2)}, \dots\dots, v^{-1}(\,v^{-}X^T y_{N)})\right] \tag{16}$$

CVaR of losses$W_\beta(\Lambda)$ is the expectation of losses conditioned on exceeding or being equal the $\xi_\beta\,(\Lambda)$

$$\mathrm{K}(\Lambda) = CVaR(\Lambda) = \omega_\beta(\Lambda) \tag{17}$$

$$\omega_\beta(\Lambda) = \frac{P[\Lambda\in R{:}\Lambda\ge\xi\;\;_\beta\,(\Lambda)]}{1-\beta}\; E\left(\Lambda \vdots \Lambda \ge \xi_\beta\,(\Lambda)\right) + \left\{1 - \frac{P[\Lambda\in R{:}\Lambda\ge\xi_\beta\,(\Lambda)]}{1-\beta}\right\}\xi_\beta\,(\Lambda)$$

Where

$$\omega_\beta(\Lambda) = \;E\left(\Lambda \vdots \Lambda \ge \xi_\beta\,(\Lambda)\right)\; if\; P\left[\Lambda \in R{:}\, \Lambda \ge \xi_\beta\,(\;\Lambda)\right] = 1-\beta$$

Concerning the minimum level of CVaR is achieved by minimizing the following:

$$Min_{x,\xi,z}\omega_{\beta}(\Lambda) = \xi + \frac{1}{(1-\beta)^N}\sum_{j=1}^{N} Z_j \quad (18)$$

$$v^{-1}\left(v^{-}X^T y_j\right) - \xi - Z_j \leq 0$$

$$v^{-1}(v^{-}X^T\bar{y}) \leq \rho$$
$$X^T\rho = v$$
$$X \geq 0$$
$$Z_j \geq 0$$

Z_j is an auxiliary variable that is used to selecting the $[\wedge -(\wedge), 0]$ Max ξ_β in the above model This is because when we proceed per definition, is the expectation $\omega_\beta(\Lambda)$ of losses conditioned on exceeding or being equal to the ξ_β (Λ).

DISCUSSION

Optimal portfolio selection is based on maximizing returns for a given level of risk. We are using in this study three risk measures and those are (Variance, VaR, and CVaR). To calculate the risk measures, sample PDF must be specified. PDF can be specified using various scenarios analytical techniques which depends on various assumptions. We produce PDF simulations using historical end of day price distribution of loss function. The study then used individual investors' trading data to get the PDF function to be used for optimal portfolio formation without assuming any specific distribution of loss function. After obtaining the sample PDF of losses, it is possible to optimize the portfolio selected using QPSO by minimizing the three risk measures mentioned earlier, and those are (Variance, VaR, and CVaR).

The goal is to assess the effectiveness of using individual investors' data as the training points in the QPSO algorithm to select optimal portfolios for short-term investment horizons. The study began by developing the optimal portfolios' benchmarks using historical market data as the training data for the QPSO algorithm, then formed optimal portfolios using individual investors' trading data as the training data for the QPSO algorithm. The study used one full year's end-of-day historical data from June 2013 to June 2014 to develop the optimal portfolios' benchmarks. The study used individual investors' trading data from June 2013 to June 2014 to develop optimal portfolios for short-term investment horizons. These optimal portfolios are then compared to the benchmarks using the three risk measures described earlier. Then, the study developed four different short-term scenarios to compare the optimal portfolios' benchmarks using historical data to the optimal portfolios' using individual investors' trading data.

In this paper, we to test the contribution of the use of individual day trading data sets for choosing optimal portfolio for short-term investors. We randomly picked 50 stocks from the US market that have positive return distributions and then fed them into the QPSO algorithm for optimization. Please note the optimization technique produces the weight of each stock in the portfolio that satisfies the constraints of the functions.

In both table 7 and table 8, the loss levels are displayed as positive numbers in the table. Gains are indicated as negative numbers to fit the coded algorithm. Table 7 shows the results of optimal portfolio selection using historical data. Table 7 reveals that the actual loss ranges from (0.019 to 0.031) in a 3-day period, but gains are ranging from (0.43 to 0.48) over four days, from (0.73 to 0.88) over five days, and from (0.51 to 0.56) over six days. As is shown in Table 8 compared to Table 9, there are no actual losses, and the gains are larger across all three risk measures. Table 8 lists the results of optimal portfolio selection using individual investors' data. Table 10 indicates that the gains range from (0.13 to 0.38) in a 3-day period, (0.8 to 1.42) in a 4-day period, (0.98 to 1.29) in a 5-day period, and (0.66 to 0.93) in a 6-day period. Based on Table 7 and Table 8, the study can conclude that individual investors' trading data are best suited to developing an optimal portfolio for short-term investors, especially for 3-day trading periods. We come to that conclusion because individual investors trading data carry with them the behavioral biases for those investors, so they contribute to the market noise and hence useful in short term portfolio optimization.

TABLE 7

The portfolio weights are shown after the stock (%). We randomly picked 50 stocks to be optimized. The loss levels are displayed as positive numbers in the table, while gains are indicated as negative numbers.

RESULTS OF OPTIMAL PORTFOLIO SELECTION USING DAY INVESTORS DATA

	Investing horizon	3 Days	4 Days	5 Days	6 Days
Variance Minimization		Stock X (15.3) Stock Y (69.8) Stock C (14.9)	Stock X (3.6) Stock Y (81.2) Stock C (15.2)	Stock Y (88.6) Stock C (11.4)	Stock X (20.1) Stock Y (54.7) Stock C (17.4) Stock K (7.8)
	Portfolio Actual loss	0.31	-0.48	-0.88	-0.56
	Standard deviation	0.25	0.19	0.2	0.14
CVaR 99% Minimization		Stock X (4.2) Stock Y (86.5) Stock T (4.4) Stock M (4.9)	Stock X (11.9) Stock Y (88.1)	Stock X (8.2) Stock Y (91.8)	Stock X (8.7) Stock Y (75.1) Stock T (16.2)
	Portfolio Actual loss	0.19	-0.46	-0.73	-0.51
	Portfolio VaR	3.64	4.34	5.18	4.88
	Portfolio CVaR	3.4	4.42	5.53	5.09
VaR 99% Minimization		Stock X (12.6) Stock Y (60) Stock C (27.4)	Stock X (3.6) Stock Y (76.4) Stock C (21)	Stock X (16.6) Stock Y (61.7) Stock C (21.7)	Stock X (18) Stock Y (53.4) Stock C (18.1) Stock K (10.5)
	Actual loss	0.22	-0.43	-0.86	-0.52
	Portfolio VaR	3.8	4.1	5.26	4.6
	Portfolio CVaR	3.63	4.67	5.95	5.51

TABLE 8
RESULTS OF OPTIMAL PORTFOLIO SELECTION USING DAY INVESTORS DATA

	Investing horizon	3 Days	4 Days	5 Days	6 Days
Variance Minimization			Stock W (17.8)		
			Stock K (8.6)		Stock U (44.7)
		Stock W (36.2)	Stock N (8.7)	Stock U (22.8)	Stock Z (3.4)
		Stock N (3.9)	Stock H (61.1)	Stock F (23.6)	Stock F (48.3)
		Stock H (60.8)	Stock R (3.8)	Stock H (53.6)	Stock K (4.2)
	Portfolio Actual loss	-0.38	-1.25	-1.09	-0.66
	Portfolio Standard deviation	0.07	0.05	0.06	0.03
CVaR 99% Minimization			Stock W (29.5)		
			Stock K (2.3)		
		Stock W (32.21)	Stock N (33.6)	Stock W (8.9)	Stock S (11.2)
		Stock N (30.7)	Stock H (24)	Stock F (46.5)	Stock F (36.15)
		Stock H (37.9)	Stock R (10.6)	Stock H (44.6)	Stock H (52.65)
	Portfolio Actual loss	-0.13	-0.8	-0.98	-0.69
	Portfolio VaR	0.26	-0.02	-0.34	-0.41
	Portfolio CVaR	0.21	0	-0.24	-0.48
VaR 99% Minimization			Stock U (3.7)		
		Stock U (2.6)	Stock W (12.1)		Stock U (41.1)
		Stock W (27.3)	Stock K (9.5)	Stock U (24)	Stock Z (2.9)
		Stock G (4.96)	Stock H (65.44)	Stock F (18.7)	Stock F (44.6)
	Optimal portfolio	Stock H (65.14)	Stock R (9.26)	Stock H (57.3)	Stock K (11.4)
	Portfolio Actual loss	-0.39	-1.42	-1.29	-0.93
	Portfolio VaR	0.17	-0.11	-0.36	-0.46
	Portfolio CVaR	0.42	0	0.14	-0.43

CONCLUSION

The study examined individual investors trading patterns and their performance. The full sample results reveal that the average individual investor in this sample can earn small but statistically significant profits. Additionally, the best-performing investors could win a sizeable mean profit of $46,421 per trade, and this is statistically significant. However, the worst performing investors did not fare as well, losing -$38,904.8 per trade. The study reveals that individual investors exhibit the disposition effect and therefore that explains the wide range difference between winners and losers in the sample.

The study then investigated optimization techniques based on historical data and the use of individual investors' trading data as the training points in the Quantitative Particle Swarm Optimization (QPSO) algorithm, and it found that the latter produced better optimization results for short-term investment horizons.

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