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Behavioral Finance Explanation of Retail Investors' Approach to Portfolio Design

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ABSTRACT

The digital space facilitates individuals' access not only to securities, but also to information that can influence their decisions. When making decisions about selecting securities to include in an investment portfolio, individual investors strive for rationality, but are influenced by various behavioral factors that increase as the digital space expands. We assume that, in addition to profitability and risk, decisions about selecting securities for investment are influenced by various behavioral factors, fundamentally shaped by motives of thrift and caution in combination with fear of missing out (FOMO) and other phenomena described in the theory of behavioral finance. We test an approach that allows us to assess, without resorting to sociological tools, the degree of significance and potential influence on the choice of a retail investor of such parameters as the affordability and liquidity of securities. Our approach is to design a profitability and risk ranking of securities included in the MOEX-40 index, and to incrementally adjust the ranking by affordability and liquidity in indicators various combinations. An instrument's rank change compared to the base ranking is a measure of the factor significance from the point of view of a quasi-rational retail investor. We have empirically shown that relatively more expensive lots are prone to more significant decrease of investment appeal that in some cases cannot be compensated by higher returns. The developed framework can be used by portfolio managers and issuers to assess the potential demand for securities by retail investors, to explain and predict their antipathy to relatively more expensive instruments. The result of the study can also serve as a theoretical justification for splitting expensive shares in order to increase their attractiveness for retail investors.

Keywords: behavioral finance; security ranking; affordability of securities; liquidity of securities; liquidation speed; retail investor; quasi-rational choice; risk diversification; retail investor portfolio; digital space

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INTRODUCTION AND PROBLEM SETUP

We begin with the quotation of R. Thaler (1999): "In the future, financial economists will routinely incorporate as much "behavior" into their models as they observe in the real world" [1]. The key postulate of the behavioral finance theory is based on the assumption that it is possible to develop investment strategies that take advantage of individuals' not fully rational behavior thus providing additional returns in excess of those predicted by EMH-based models. However, beyond the irrationalities explained by the provisions of prospect theory [2] or cognitive errors, investment decisions are also driven by rational motives, including risk appetite and thrift, which are, according to [3], especially acute during crises.

The decision to invest in securities requires a retail investor to choose specific instruments. Behavioral phenomena — panic and hype, FOMO, responsibility sharing, and verification of decisions by public opinion — are catalyzed in the digital space due to the high speed of information dissemination [4]. This is why individual investors are initially not rational, but quasi-rational due to the large contribution of uncertainty [5] in decision-making. They will seek to diversify the portfolio, i.e., buy several instruments, and in a multiple-choice situation, they will use standard approaches: maximize the expected return by extrapolating data on retrospective returns. Then, following the logic underlying prospect theory, the selection will include securities that have demonstrated high growth rates and/or low volatility in the recent past.

An alternative tactic of a quasi-rational investor is to study the rankings of securities in order to design a portfolio. This tactic is based on the generally correct assumption that a ranking is compiled by stock market professionals, and therefore is more reliable than the conclusions obtained by an individual independently. In this case then, the portfolio will include n securities with the best rank.

Thus, for portfolio managers and issuers targeting retail investors, it may be fundamentally important to understand whether a retail investor will *ceteris paribus* choose this particular instrument, and what will be the factor determining this choice. It will be no less important to identify the factors of negative choice ("I will definitely not buy this stock"). Presumably, an issuer and a portfolio manager seeking to ensure portfolio liquidity and diversification of security holders, will be interested in promoting a security upwards in a risk-return ranking.

If the selection includes instruments with a lot price exceeding the limit set by the investor or undermines diversification opportunities, a quasi-rational investor will certainly censor the portfolio, getting rid of securities that over concentrate risk in one instrument or are unavailable due to their high cost. The liquidity motive is also important: the ability to quickly sell an asset at a fair price is perceived by individual investors in strict correlation with a lot price. From a fundamental point of view, a high lot price is a restraining factor for the market during periods of market imbalance towards fear (according to the fear and greed index), which makes such lots less attractive for retail investors, who, according to Gomez Martinez et al. [6], are influenced by the news background, or, as noted by Dash & Mishra [7], by the social media sentiment regarding the news.

Our task is to establish, without resorting to sociological tools, how the liquidity of a security influences the decision to buy. The following hypothesis will be investigated: a lot price and a lot liquidation speed have a significant impact on a stock's position in a ranking and, therefore, on the probability of this stock being included in a retail investor's portfolio.

The hypothesis is based on the following ideas. Along with the irrational behavior of investors, who are driven by greed and fear, they also have rational motives, which also fit into the existing tradeoff between the market efficiency hypothesis and the theory of behavioral finance. A rational investor, driven by the "constructive" or "positive" greed, will buy what is cheaper or what is easier to sell; yet, presumably, "easier to sell" does not necessarily mean "cheaper". And thrift will restrain the investor from buying a more expensive lot.

To formalize the motives, it is necessary to decompose the empirical approach to securities comparison in the space of "more attractive — less attractive" to derive theoretical assumptions about how significantly the fear and greed motive will impact the choice of shares, how to predict the choice of a retail investor (including a negative choice), and explain why some securities may not obviously be more or less popular among retail investors.

METHODOLOGY AND THEORETICAL BACKGROUND

Theoretical Approaches to Comparison of Stocks

Consider a standard comparison framework that fits into the logic of securities rating models. The task of rating securities in a generalized formulation is not new either from a scientific or practical point of view. Several approaches have been developed and applied to date, each of which has many cases of practical implementation. However, only two fundamental tasks are attributable to ratings: the task of securities classification according to established criteria and the task of their comparison (ranking).

More common in public and professional discourse are classification ratings of issuers and/or issues of securities, which are based on the fundamental characteristics of the operating and financial activities of an economic entity. Such ratings are aimed at assigning an issuer or its securities to a certain quality category that meets specified criteria, while the task of comparing two or more securities is not applicable in this context: securities with the same rating are considered as equally acceptable for certain management purposes (for example, for the initial selection of securities when shaping a portfolio). At the same time, there is a consensus that shares with the same rating can be subject to qualitative comparison in the category space of "worse — better", "more attractive — less attractive", etc., which opens up opportunities for the second previously mentioned rating area.

Known approaches to comparative multi-criteria stock rating operate with such characteristics as profitability (r, relative change in stock price over a period) and risk (σ, standard deviation of a series of returns over equal periods), which are positively correlated, while the target criteria for them are opposite: maximization of profitability and minimization of risk.

A graphical interpretation of the problem of comparing shares in the coordinate system of risk and profitability (r, σ) is presented in *Fig. 1*.

Thus, if there is a choice between shares A, B, C and D, then share C will be characterized by the highest return and the lowest risk. The problems of pairwise comparison of shares lying on the lines of orthogonal projections on the axes also have an obvious solution: of the two shares with the same return (for example, C and D), the one with the lower risk (share C) will have a higher rank, and, conversely, of the two shares with the same risk (for example, A and D), the higher-yielding share (share D) will have a higher rank. The results of comparing shares lying in the risk and return space on the same descending line (see, for example, shares A and C) are just as easy to interpret: the share that is located to the left along the horizontal axis will have a higher rank.

The key problem of comparative analysis is ranking stocks lying on ascending "diagonals" (e.g., choosing between members of pairs BD, BE, DE, CE, AE or multiple choice). The theoretical solution refers to the calculation of additional characteristics, such as return per unit of risk (r / σ), and to an analytical study of the dependence of return on risk in order to determine the slope (regression coefficient) of the $r = f(\sigma)$ graph: as shown in *Fig. 1*, the slope of the r_b line is greater than the slope of the r_a line ($a < b$), which can ensure a higher rank of stock E compared to stock D, because the increase in E's risk is followed by a more significant increase in its return.

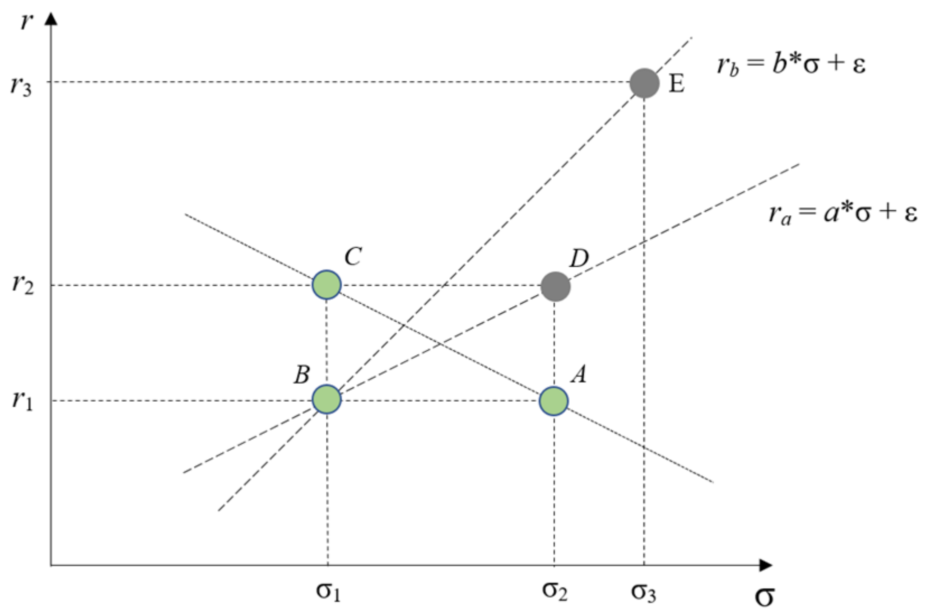


Fig. 1. **Graphical Interpretation of the Problem of Comparing Stocks by Combination of Risk and Return**

Source: Visualization made by the authors.

It should be noted that the investment strategy (conservative — stock B, or aggressive — stock E) and the permissible limits of risk appetite play a decisive role in this choice. From the point of view of the latter criterion, it is possible that out of the BD pair, share D will have a lower rank just because of the excessive risk for this investor. Consequently, it turns out that the solution to the problem of multiple shares' risk and return classification is largely **subjective**, and, therefore, an additional measurable criterion is required.

Moreover, the described approach does not exclude the possibility that there is, for example, share C*, which has the same risk and return values as share C. Obviously, the equality of the risk and return values of the two shares does not provide grounds for concluding that they are identical, without any analysis. Then the choice of a security will be driven by other criteria that a rational retail investor is guided by under normal conditions (beyond panic-driven or hype-driven markets).

The previously stated hypothesis is based on the assumption that, if the risk and return of two securities are equal, a retail investor will most likely buy the one that is cheaper or the one that is more liquid. This approach is rational in many ways, but it may encounter a contradiction between low price and liquidity.

LIQUIDITY OF SECURITIES: PRACTICAL APPROACH TO FORMALIZATION

Our suggestion is to develop the framework of securities ranking by adding the third dimension — liquidity, in the definition of which there is significant pluralism due to the different approaches present in the discourse (economic, financial, institutional, etc.) and the tasks by which this category is employed.

A widely used approach in financial research is to define liquidity as a relative measure of an asset's price change which is required to sell it [8]. Liquidity as an attribute is evident through a security's high trading volume and a relatively small spread between bid and ask prices. Since a rational investor will consider it safer to invest in liquid assets rather than in illiquid ones, the expected return on an illiquid asset should be higher to compensate for the presence of transaction costs. Following the described approach, a formalized representation of liquidity will be a relative spread between the bid and ask prices [9] or the ratio of the absolute change in price per day to the daily trading volume of an instrument. The CAPM implementation of liquidity adjustment can be obtained from Altay & Çalgici [10] or Alves et al. [11].

Notable is the approach, according to which liquidity is considered one of the determinants of stock returns and a factor explaining differences in returns. In line with this approach Datar et al. [12] used the ratio of the number of shares traded to the total number of shares outstanding as an indicator of a stock's liquidity.

In retrospect, the trading volume can be used to assess the liquidity of a security: the higher the trading volume during the day, the more liquid the security is considered. This approach has a number of theoretical limitations, including its inability to take into account absolute differences in lot prices, which can potentially make expensive securities less liquid, despite the high trading turnover provided, for example, by institutional investors. This circumstance is an argument in favor of the need to specify the procedure for applying liquidity indicators of listed shares.

In this study, we will adhere to the approach declared by the Moscow Exchange, according to which the liquidity of a security is "the ability to quickly exchange a security for cash without loss of value or with minimal loss of value." This definition is consistent with the approach of A. Damodaran, who links the speed of selling an asset with the need to provide a discount to the buyer, which is a transaction cost that ensures a loss of value; he calls the lack of liquidity a situation in which the holder is unable to sell the asset immediately [13]. In this regard, it can be assumed that the speed of selling an asset is affected by the attractiveness of the issuer and the security itself, as well as the affordability of the share to retail investors, expressed in the absolute price of the lot: the lower the lot price, the greater the number of potential investors to buy it.

The next step taken was to introduce and discuss several liquidity metrics.

1. Affordability expressed as a lot price (P_L) — a product of a security's price and its lot size.

For example, as of the last trading day of October 2022, lot prices of MOEX-40 constituents varied from 168.4 rubles (VTB) to 96,700 rubles (Transneft). At the same time, 21 of the 40 instruments were traded at a price of less than 1,000 rubles per lot; 11 instruments were traded at a price of over 2,000 rubles per lot. *Fig. 2* shows the distribution of lot prices of the MOEX-40 index constituents excluding the outliers — Transneft preferred shares (96,700 rubles per lot), and Norilsk Nickel ordinary shares (13,758 rubles per lot).

Given the existing significant difference in lot prices, we suggest that some instruments are less affordable to retail investors, which makes them potentially less liquid. Thus, the affordability of securities for retail investors, expressed in a lot price, is a significant factor determining the liquidity of listed securities. It was the interests of retail investors that guided the largest issuers when deciding to split shares: Tesla Motors Corp. in 2020, Alphabet Inc. in 2022, Transneft in 2023. In these and other cases, the companies' press releases emphasized the expected increase of their shares attractiveness to retail investors.

2. Daily number of deals (Q_D) and daily number of lots sold (Q_L).

This is an objective measure of a security's liquidity, reflecting the balance of supply and demand and potentially indicating the possibility of quickly closing positions on certain securities, which may be important in periods of high volatility. It is assumed that the number of deals is higher for more liquid securities ($Q_D \to max$).

It is necessary to take into account the differences in the liquidity characteristics of securities, expressed by the number of deals or the number of lots sold: theoretically, a situation is possible when a large number of lots will change possession within a single deal; in this case, a formally high liquidity assessment will be false. To level out this shortcoming, it seems justified to use the "*trading speed*" (average number of deals per minute) and the "*closing speed*" (time required to close a position),

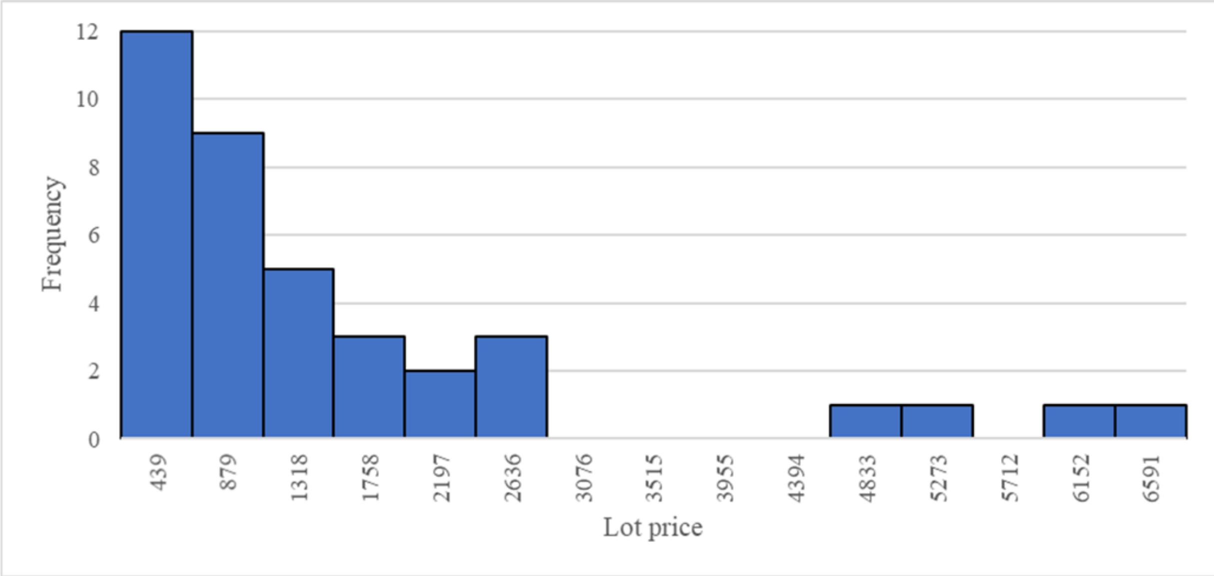


Fig. 2. **Lot Prices Distribution Chart, MOEX-40 Constituents, As of 31 October 2022**

Source: Calculations and visualization made by the authors.

as implemented in Ali et al. [14] or Anagnostidis & Fontain [15].

The calculation procedure is described in *Table 1*.

To test the above arguments' validity, we estimate the dependence of several liquidity metrics (see *Table 1*) on the lot price using the MOEX-40 constituents trading data for the one trading day (31 October 2022).[1]

The daily number of lots sold changes inversely proportional to the lot price (see *Fig. 3a*), which is generally intuitive, but there are no statistical grounds to recognize such a correlation as significant (R^2 = 23%). The influence of the lot price on trading speed (*Fig. 3b*) is also not confirmed by the data, as is the influence of the lot price on closing speed (*Fig. 3d*). Notably, the closing speed of the most expensive lots is higher (takes less time) than that of several much cheaper lots.

Yet, the lot price influence on the average worth of the deal can be considered statistically significant (*Fig. 3c*), which is true for the data sample and subject to validity tests using a wider sample and/or longer time series.

Consequently, the lot price, despite its obvious simplicity of interpretation, does not demonstrate reliability in explaining the observed spread of the liquidity indicators' values. In other words, there are insufficient grounds to assert that "cheap = liquid", "cheap = easy to sell". This goes in contrast with Będowska-Sójka's findings regarding the emerging market correlations between various liquidity proxies [16].

On the other hand, the absence of correlation can be interpreted as follows: the lot price is independent of trading activity, thus **less biased towards behavioral factors**. Under certain conditions, this allows us to consider it as a **valid measure of securities' liquidity**.

The trading volume also shows no signs of statistically significant dependence on the lot price (see *Fig. 4a*). However, a statistically significant influence of the trading speed on the daily trading volume was established (*Fig. 4b*), which is generally comprehensive.

Therefore, the trading speed and its inverse characteristic — closing speed — can be used in further analysis as an indicator of liquidity (in the development of commonly agreed ideas denoted as "liquid = has a large trading volume").

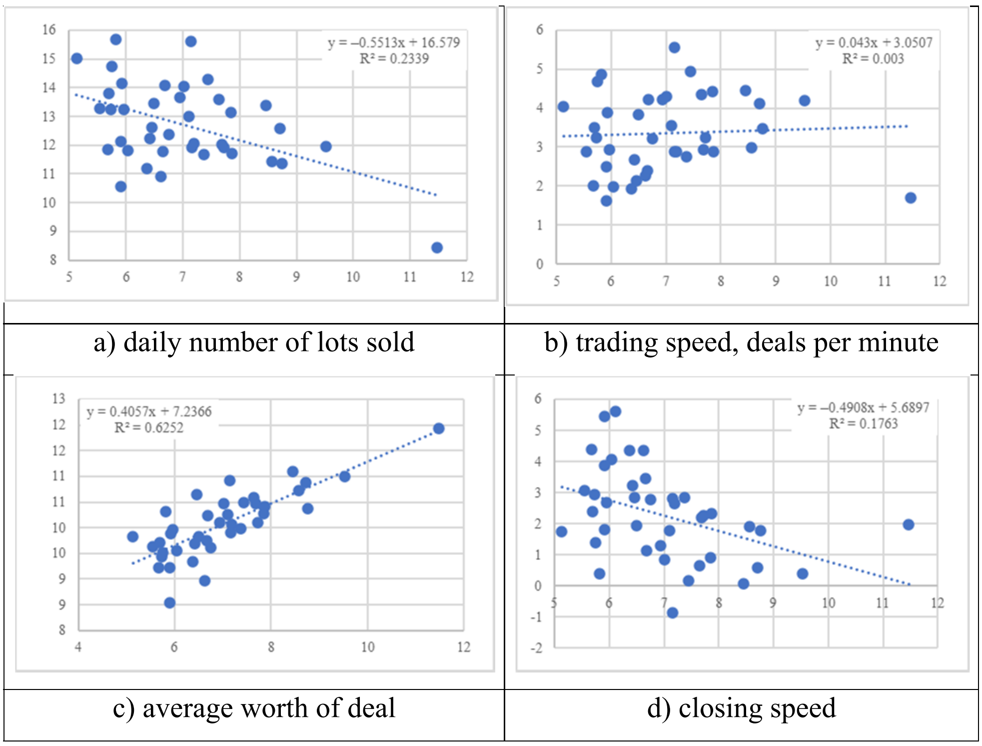
[1] Subject to further verification based on a wider sample and longer time series.

Table 1

Liquidity Indicators of Securities

Indicators	Symbol	Formula
Trading volume	V	
Average price	P	
Number of deals	QD	
Lot size	LS	
Lot price	LP	P * LS
Trading volume per deal	VD	V / QD
Trading volume as the number of lots sold	VL	V / LP
Average deal size as the number of lots sold	LD	VL / QD
Average number of deals per minute, for 9-hour long trading session	QM	QD / 540
Average number of lots sold per minute, for 9-hour long trading session	N	VL / 540
Number of lots per 100,000 rubles	K	100 000 / LP
Closing speed per 100,000 rubles worth of lots held, seconds	T	60 * K / N

Source: Proposition introduced by the authors.



a) daily number of lots sold

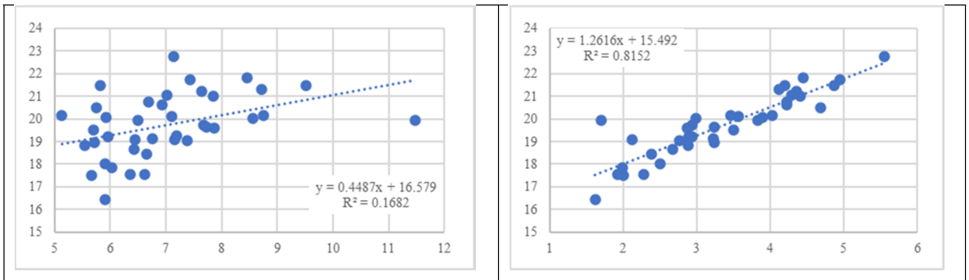
b) trading speed, deals per minute

c) average worth of deal

d) closing speed

Fig. 3. **Scatterplot of Liquidity Metrics Against Lot Prices (Horizontal Axis), LN-Transformation Applied**

Source: Calculations and visualization made by the authors.



a) trading volume dependence on the lot price	b) trading volume dependence on trading speed

Fig. 4. **Trading Volume Dependence on the Lot Price and Trading Speed, LN-Transformation Applied**

Source: Calculations and visualization made by the authors.

RESULTS AND DISCUSSION

We model the impact of the lot price and closing speed on a security's risk-return rank. Assume that an investor's primary selection of *n* best securities, based on a ranking of shares by yield and risk, will change if liquidity is implemented in the ranking methodology. To verify, we use MOEX-40 constituents' data as of 31 October 2022.

Four ranking options were calculated, in each of which the indicators used have equal weights:

- P1: yield and risk (standard deviation of yields);
- P2: yield, risk and affordability (LN-transformed lot price);
- P3: yield, risk and liquidity (LN-transformed closing speed);
- P4: yield, risk, affordability and liquidity.

The ranking methodology is based on the relative scaling of the values of the rated indicators according to the following:

$$S_{a,i} = w_1 S_{1,i} + w_2 S_{2.i} + \ldots + w_n S_{n,i}\text{; } S_a \to \max;$$

$$S_{n,i} = 1 - \frac{(v_i - v_{min})}{(v_{max} - v_{min})}$$ For descending series (minimum value is considered best)

или

$$S_{n,i} = \frac{(v_i - v_{min})}{(v_{max} - v_{min})}$$ For ascending series (maximum value is considered best),

where Sa — total ranking score of an item i, i $\in$[1; k]; S_n — ranking score of an item i by an indicator n; w_n — weight of a ranking score Sn as a fraction of 1 $\sum_{j=1}^{n} w_j = 1$; v_i — value of an indicator for element i, i $\in$[1; k].

The item having maximum value of Sa gets rank "1", and the minimum value — rank "k".

Since yield and standard deviation are relative indicators, there is no need to normalize their values: the sum of the scaled values of all items is 18.6 for the yield and 28.9 for the risk, which indicates that the scores are aligned relative to the conditional center (20 out of 40).

The spread of scores for the lot price and closing speed is shifted towards the maximum due to significant absolute differences between the maximum and minimum values (38.4 and 35.8, respectively). To level out the contribution of outliers to the spread of values on the relative scale, logarithms were used. As a result, the sum of scores for the lot price was 28.3, and for the closing speed — 20.6.

For the purposes of ranking, a historically weighted approach to calculating the yield was used: earlier values had less weight, while greater weight was assigned to the returns for the most recent period. Rank "1" corresponds to the highest yield.

Formalization follows:

$$R = 1 + 0{,}4r_{2022} + 0{,}3r_{2021} + 0{,}2r_{2020} + 0{,}1r_{2019}\,,$$

$$r_y = \sqrt[12]{\prod_{m=1}^{12} r_m}\,,$$

Table 2

Spearman's Rank Correlation Coefficients

Parameters	Yield	Risk	Lot price	Closing speed
Yield	1	0.271	−0.363	0.080
Risk	0.271	1	−0.137	−0.003
Lot price	−0.363	−0.137	1	−0.480
Closing speed	0.080	−0.003	−0.480	1

Source: Calculations made by the authors.

Table 3

Ranks of the Select Securities (Rank "1" Corresponds to the Highest Rank)

Feature	ISIN	Security	Rank with the model			
			P1	P2	P3	P4
Maximum yield*	RU 000A0JRKT8	PhosAgro, common stock	1	5	1	4
Minimum yield	JE 00B 6T5S 470	Polymetal	38	37	37	37
Most expensive lot	RU 0009091573	Transneft, pref. stock.	11	38	15	36
Cheapest lot	RU 000A0JP5V6	VTB, common stock	34	21	32	20
Most volatile	US 5603172082	VK Company Limited, GDR	40	40	40	40
Least volatile	RU 000A0JUG31	Moscow Credit Bank, common stock	3	2	4	1
Most liquid	RU 0009029540	Sberbank, common stock	32	30	7	8
Least liquid	US 5603172082	VK Company Limited, GDR	40	40	40	40

Source: Calculations made by the authors.

Note: * – Here and further in *Table 3* – as per the sample over the given period and using the methodology applied.

$$r_m = \frac{P_m}{P_{m-1}},$$

where R — historically weighted yield of an instrument; r_y — average yield of an instrument in the year y; r_m — monthly yield m; P_m — closing price in the last trading day of a month m.

The standard deviation of yields was obtained from the calculated rm values. Rank "1" corresponds to the minimum standard deviation.

The lot price for ranking purposes is calculated as the product of an instrument's closing price on 31 October 2022 and the size of its lot. Rank "1" corresponds to the minimum lot price.

The closing speed is also calculated based on the 31 October 2022 data using the methodology described in Table 1. Rank "1" corresponds to the minimum time required to close a position.

The weights, as well as the retrospective duration, can be changed and, presumably, do affect the final rank, which, however, is not the subject of this study.

The low correlation of the securities' ranks across the four indicators is noteworthy. Thus, the Spearman's rank correlation coefficient

Table 4

Ranking Change Summary (Ratings P2 – P4 Compared to Rating P1)

Description	Lot price added (P2 – P1)	Closing speed added (P3 – P1)	Both lot price and closing speed added (P4 – P1)
Rank unchanged, number of instruments	2	3	5
Rank increased, number of instruments	22	17	18
Biggest increase of a rank, absolute rank change	13	25	25
Rank decreased, number of instruments	16	20	17
Biggest decrease of a rank, absolute rank change	27	22	25

Source: Calculations made by the authors.

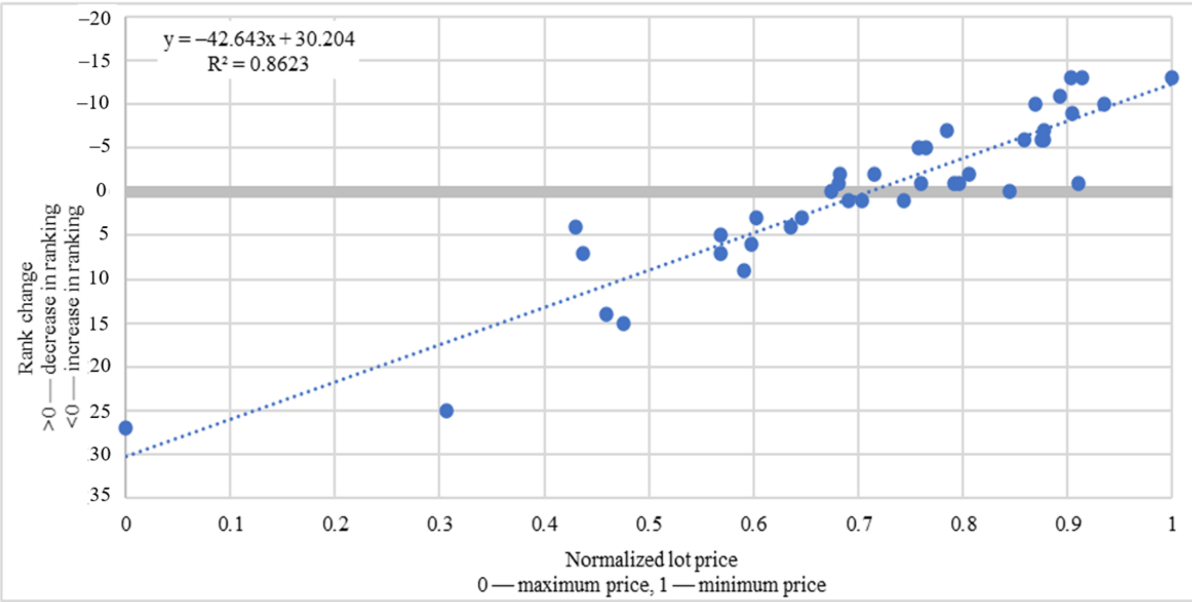


Fig. 5. **Scatterplot of Absolute Changes in Securities Ranks Depending on the Normalized Lot Price**

Source: Calculations and visualization made by the authors.

highest value (–0.48) is noted between the ranks of securities by the lot price and closing speed, which can be interpreted as partial confirmation of the seemingly obvious argument: what is cheaper is sold faster, — and as its refutation, since for more than half of the observations this conclusion does not apply. At the same time, the ranks by closing speed are not correlated with the ranks by yield and risk (see *Table 2*).

Analysis of the Spearman's rank correlation coefficients allows us to conclude that the ranks by the four indicators are not mutually determined. Consequently, the employed approach to ranking is valid in any combination

Table 5

Spearman's Rank Correlation Coefficients

Rankings	P1	P2	P3	P4
P1	1	0.695	0.675	0.609
P2	0.695	1	0.321	0.681
P3	0.675	0.321	1	0.814
P4	0.609	0.681	0.814	1
Yield	0.763	0.534	0.580	0.542
SD of Yield (risk)	0.758	0.584	0.490	0.466
Lot price	−0.353	0.321	−0.535	−0.037
Closing speed	0.052	−0.216	0.674	0.490

Source: Calculations made by the authors.

of the indicators used (see rating models P1 — P4 above).

The P1 ranking will be used as the benchmark to assess an instrument's rank change if affordability and / or liquidity considered. Refer to *Table 3* for the select securities ranks across different characteristics.

It is obvious that adding the affordability and liquidity indicators to the ranking negatively affected the rank of the most profitable security, while its rank did not change when adding only the closing speed. The rank of the most expensive security (P1 = 11) predictably turned out to be very sensitive to the lot price (affordability), making it decrease to 38th place in P2. At the same time, this stock is quite liquid, so its rank in P3 did not decrease significantly — by only 4 positions. However, in a combination of availability and liquidity, the former, taking into account the equality of weights, undermines the support from liquidity, as a result of which the rank of this instrument decreases to 36th place.

We see that adding the affordability and liquidity indicators to the ranking benefits the lowest lot price securities (for example, ordinary shares of VTB) and the fastest-to-sell ones (for example, ordinary shares of Sberbank): the first moved up in the ranking by 14 positions, the second — by 24 positions. See *Table 4* for aggregate data on rank changes.

Obviously, consideration of affordability has a significant impact on a security's risk-and-return rank: as the lot price decreases (affordability increases), the rank increases (see *Fig. 5*).

The pattern of risk-and-return rank changes in the case of adding the "closing speed" parameter is generally the same.

The calculated values of the Spearman's rank correlation coefficients (see *Table 5*) indicate that the correlation of the ranks under P1 and the "lot price", as well as P3 and the "lot price" is negative, and in the second case, it is significant. That is, as the rank value by the lot price increases, the risk-and-return rank decreases.

CONCLUDING REMARKS

Thus, it has been empirically proven that cheaper and more liquid securities will rise in the risk-and-return ranking above the expensive lots, taking into account their affordability for a retail investor. On the contrary, securities that are characterized by more expensive lots will fall in the risk-and-return ranking much more dynamically, taking into account their lower affordability for retail investors.

Consequently, the ranking of securities by yield, risk, affordability, and liquidity indicators is an effective tool for comparative assessment of the investment attractiveness of the listed securities: for a quasi-rational investor, the place of a security in the ranking is a reliable guide for determining the composition of a portfolio; for a portfolio manager and for an issuer, it is an indicator of which security a retail investor is most likely to buy, and, finally, for academia — a contribution to the explanation of managers' behavior, as denoted by Nikiforow [17].

Taking into account the principles of behavioral finance theory, the approach to comparative ranking of securities will allow us to explain with greater reliability the reasons for the greater or lesser popularity of certain securities among investors, to explain their choice, and to formalize the decision-making process in conditions of obvious differences — one of the tasks developed by Schiller [18]. Having an integral characteristic of risk-return-liquidity, a retail investor, rational and irrational, will be guided by liquidity data, comparing two or more securities in the case of an exceptional choice. After due verification, the approach substantiated in this work can be used as a basis for value management strategies on the issuer's side.

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S.V. Polyakov — data collection and preparation, behavioral finance literature review, ranking model setup and computation, results interpretation.

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