CONFERENCE PROCEEDINGS/FULL PAPERS
ISBN: 978-625-93894-9-3/April 2026

"46th RSEP International Conference on Economics, Finance and Business" 17-18 April 2026, Hotel Campanile Paris La Villette, Paris, FRANCE"

From Intuition to System: An Institutional Approach to Retail Investing

Mikhail Urinson
Chief Investment Officer and Data Scientist, Legacy Quant | ARK Quant Crypto, Miami, USA
E-mail: mao@arkquantcrypto.com

DOI: https://doi.org/10.19275/RSEPCONFERENCES389

Abstract

The article undertakes the transition from gut feeling to a system of trade selection based on the institutional discipline. It aims at providing a theoretical justification and an applied formalization of this transition by observing market regimes, behavioral biases, and a set of filters for selecting an asset based on quantitative filters and metrics. The relevance of the study lies in the expansion of private investor participation in a more complex market environment, where the roles of algorithmic trading, social platforms, and the costs of decision-making errors have intensified. The scientific novelty of the article lies in transferring the institutional framework of capital management into the practice of retail investing and in integrating market regime diagnostics, a proprietary PPM indicator (Price Pressure Momentum), a historical-signal robustness rating, and behavioral controls into a unified IDW-RQI model. The main findings indicate that such a system increases decision reproducibility, reduces sensitivity to market noise, limits participation during adverse market phases, and improves the portfolio's risk profile relative to passive investing. The article will be useful to modern financial advisors, financial market researchers, private investors, instructors, and developers of quantitative investment strategies.

Keywords: retail investing, institutional discipline, quantitative methods, market regimes, noise filtration.
JEL codes: L81

1. Introduction

The architecture of financial markets during the period 2020–2026 underwent a transformation driven by the democratization of access to capital and the simultaneous complication of market microstructure (Eaton et al., 2022). Under conditions in which algorithmic trading accounts for the majority of institutional volume, most investment decisions are made through systematic rules and complex mathematical models (Tudor & Sova, 2022). The retail segment, despite the sharp growth in participation, often remains captive to an intuitive approach based on emotional reactions, social signals, and fragmented data (Warkulat & Pelster, 2024).

The relevance of this study stems from the need to close the gap between institutional standards for capital management and private investors' practices. Since 2020, a paradox has been observed. Access to markets has become almost unlimited and free. These mistakes are more costly for the unprepared investor due to market volatility and the herding effect, which is exacerbated with social media (Li et al., 2023). The services available to the retail investor can be weak when compared to hedge funds, which still have unfettered access to resources (Chen et al., 2025).

This article seeks to develop a theoretical rationale as well as a practical formalization of the transition from intuitive trading to systematic quantitative trading. To achieve this aim, the study addresses the tasks of classifying market regimes, analyzing the influence of digital platforms on investor behavior, and verifying the effectiveness of proprietary quantitative indicators such as PPM (Price Pressure Momentum) and ER (Effectiveness Rating). The study's scientific novelty lies in integrating the concept of institutional discipline into an adaptive retail workflow that uses machine learning to detect latent market states.

2. Materials and Methodology

The article's material consisted of recent scholarly publications on retail investing, algorithmic trading, behavioral finance, and market regimes. Reports from financial regulators and international organizations were also used, which describe changes in market structure and the growing role of private investors.

In methodological terms, the article is structured as a combination of a source review and an examination of an applied trade-selection model. At the center of attention lies the transition from intuitive decisions to a consistent system of rules. For this purpose, several elements are considered: market condition, trend direction, the strength of price movement, and the historical reliability of the signal.

To analyze market states, the article uses machine learning models that enable it to classify the market into growth, decline, and stress phases. The main emphasis is on hidden Markov models and mixture distribution models. These instruments are needed to determine the market regime and whether entry into a position is permissible. After that, three filter groups are applied. Moving averages help verify trend alignment across daily and weekly intervals. The PPM indicator is used to assess the strength of the movement. The ER indicator shows how stable a given signal has been over a available history (in some occurrences 30 - 40 years back) which makes it statistically significant.

The operational validity of the approach is demonstrated through a simulated comparison of a systematic portfolio with a passive allocation to a broad-market index, using data for 2015–2025. One part of the methodology involved dividing the sample into training and validation sets to assess whether the system retains useful properties under changing market conditions. The evaluation took into account return, volatility, drawdown depth, efficiency ratio, and the stability of monthly results.

3. Results and Discussion

Historically, trust management and private investing were perceived as a form of art grounded in experience, intuition, and personal relationships. During the 2020s, this paradigm gave way to the age of Quant, quantitative analysis, where success is determined by the discipline of execution and the quality of the process (Poudel & Paudel, 2025). Intuitive investing is vulnerable to cognitive distortions such as the fear of missing out (FOMO) or panic selling at the first signs of a correction (Klepacki, 2025).

The institutional model is built on a recurring cycle: data collection, noise filtration, edge verification, portfolio construction, and results audit. In this system, the best decision is often to do nothing when the market regime does not align with the strategy's parameters. The transition of a retail investor to such a model requires introducing behavioral control, a set of rules that limits discretionary intervention in the trading process.

Studies show that retail and institutional investors react differently to market hype (Luo et al., 2025). Retail attention often serves as a contrarian indicator: a high level of search interest in a stock predicts a decline in its return during the following weeks. This is explained by the fact that private investors jump onto a departing train, buying assets at the peak of media activity, while institutions have already begun taking profits. Types of attention and their impact on returns are shown in Table 1.

Table 1. Types of Attention and Their Impact on Returns

Type of Attention	**Measurement Tool**	**Impact on Returns, Short-term**	**Mechanism of Influence**
Retail, ARA	Google Search Volume	Negative, Decline	Herd behavior, buying at the peak of hype
Institutional, AIA	Bloomberg Readership Score	Positive, Increase	In-depth analysis before the official release of news

This asymmetric balance implies that quantitative filters need to be adopted by retail investors to filter out ARAs (Abnormal Retail Attention) and focus on institutional-positioning-signal data. The Institutional Discipline for Retail Quantitative Investing (IDW-RQI) is a quantitative investment strategy based on multi-level filter indicators, which transform market noise into organized trading signals. The process is often depicted as a funnel, where candidates with low probability of success are filtered at several stages (see Figure 1).

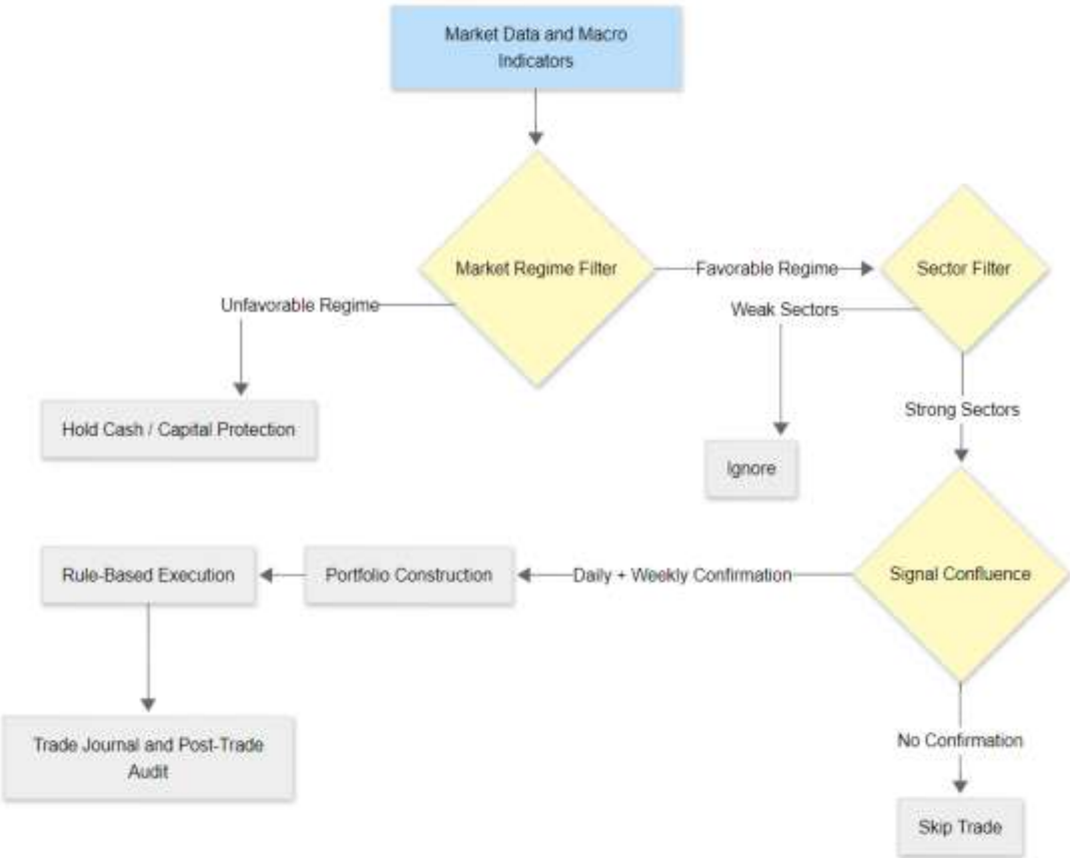

Fig. 1. Multi-Stage IDW-RQI Framework

What separates the professional from the amateur is the understanding of the context of the market. Quantitative systems will also use regime detection to control risk or stop trading.

There are four main states within the market. In the Emerging Expansion state, risky assets begin to rise while volatility remains high. Tech stocks and small capitalization stocks generally lead within this state, which has a fairly strong trend and low uncertainty. This also represents only the period where a more instinctive approach might be profitable for a while, since one might find discipline difficult initially.

The Cautious Decline state describes a regime where the risky assets display negative returns and capital migrates into gold and defensive government bonds. The Market Chaos state describes an extremely stressed regime, where the systematic approach attempts to reduce market exposure and protect the core of capital. Hidden Markov models can identify up to 9 states, which can include latent bearish periods not readily apparent due to low index volatility.

To support the reproducibility of the IDW-RQI system, three types of evidence are used to validate the outcome. The first is SMA Bands. For instance, SMA bands 10, 21, 41 (proprietory optimization model completed, may vary by instruments and market states) can be used to identify the dynamic demand and supply. The institutional approach is to validate the trend on a larger time horizon, daily and weekly, among others. If the short timeframe gives an entry signal while the long timeframe remains in a downtrend, such a signal is interpreted as false (low probability, weak).

The second type is designated as PPM, or Price Pressure Momentum. This proprietary oscillator measures the probability of price movement above or below certain levels. Its function is connected with impulse filtration. It permits entry into trades only when the accumulated kinetic energy of the movement is statistically confirmed.

The third type is designated as ER, or Effectiveness Rating. The effectiveness rating serves as a measure of a signal's historical reliability for a specific instrument. Instruments with a high ER value demonstrate pattern stability over long term (three, five, in some instance go back 30 - 40 years). The formation of portfolios from Top ER category assets helps reduce the risk of model overfitting. The sample relies on a stable regularity and does not depend on accidental coincidence.

The practical value of the institutional discipline system lies in transforming trade selection into a sequence of checks. The market regime sets the boundaries of risk. Moving averages show whether the price movement is supported on the daily and weekly intervals. The PPM (price pressure momentum) indicator separates an impulse with internal strength from a random jump. The ER indicator shows to what extent a given signal preserved working properties over a long history. Within such a scheme, the investor receives a clear order of action. First, it is determined whether the market state permits the search for an entry point. Then trend alignment is checked. After that, the movement's strength and the signal's durability are assessed. Only after passing through all stages can the asset enter the portfolio.

Consider the hypothetical example of an investor who observes the shares of a large semiconductor company following a series of strong upswing moves. The price has risen by 8% over the week. Assume that the ER for this security is medium. Then by default your allocation should be minimal, regardless of price action analysis than number of searches and discussions is increasing sharply. At the first stage, the system indicates an emerging-growth phase, so the asset is added to the watch list. During the second stage, the on the daily chart is above the SMA 10- and 21- form a golden cross, above 41-day SMA with price moving above all. The weekly chart is still in no trend zone but clearly stabilized and preparing for the breakout, indicating potential breakout, not confirming one yet. At the third stage, PPM indicator gives a positive signal, with its value raising above admission threshold. The decision outcome in this case is to wait until signal is confirmed by the weekly chart, because of medium ER, we only trade those assets that are fully aligned.

Two weeks later, the situation continues to improve. The weekly chart continues to improve above key level of suppport. The SMA lines align in ascending order on now for both daily and weekly intervals. The PPM indicator rises above the threshold level for weekly chart as well. After that, the position is opened with a predetermined amount of risk due to the ER level. ER is slow to adjust since depending on the instrument history it may consitute of many independent measurement (3-, 5-, 10- or more years). It will take a lot of succeful trades for it to rise. Due to medium ER tide stop are highly advised. If the market shifts into cautious decline, the position size is reduced, or the trade is closed according to the regime rule. Such methodology helps to enter a trade only when market direction, trend structure, movement strength, and the historical reliability of the signal form a unified set of evidence.

The effectiveness of the transition to a quantitative system was tested on data for 2015–2025. The main object of analysis consisted of portfolios constructed according to Kendall’s methodology (WT/PE) using ER and PPM filters. The table below presents the results of simulation modeling, demonstrating how institutional discipline affects the indicators of a retail portfolio in comparison with passive investment in the S&P 500 Buy-and-Hold.

Table 2. Annualized Performance Comparison, S&P 500 vs. IDW-RQI

Metric, Annualized	S&P 500, Benchmark	IDW-RQI, Systematic	Difference / Conclusion
Return	9.0%	15.2%	Moderate growth driven by asset selection
Volatility	18.0%	14.5%	Significant risk reduction
Sharpe Ratio	0.50	0.70	40% improvement in efficiency
Max Drawdown	-35%	-15%	Effective protection in 2020 and 2022 deep corrections
Win Rate	n/a	65%	The model doesn't win all the time. None of them do. But wining 65% of time is enough to demonstrate significantly improved performance.

The analysis above clearly show that the quantitative workflow generates excess return through drawdown control and through limiting participation in unfavorable regimes. Of particular interest is the transfer of the strategy from the training period (in-sample 2015–2020) to the high-volatility testing period (out-of-sample 2021–2025). Portfolios built exclusively on ER logic retained positive dynamics despite the general decline in market returns and structural shifts. This provides empirical evidence of the transferability of the construct, the ability of a quantitative system to maintain functionality under changing market conditions, including extreme ones.

The introduction of a discrete signal update regime, once per day or once per week, enabled reducing the influence of market micro-noise. In contrast to retail traders who react to each intraday price movement, the IDW-RQI system makes decisions only after the trading session closes, thereby aligning the actions of all execution participants and reducing emotional stress.

The transition to the system is complicated by the technological environment of modern brokerage applications. Studies from 2024–2026 emphasize the destructive role of gamification (DEP). Platforms use hedonic elements, e.g., confetti and achievement badges, that exert a strong influence on investors with low financial literacy (Chapkovski et al., 2024).

Experimental data show that gamification increases trading volume by 5.17%, with 70% of this activity driven by self-selection among the most gambling-prone users (Chapkovski et al., 2024). In such an environment, institutional discipline functions as a behavioral firewall.

Despite the evident advantages, the transition to quantitative methods is associated with several barriers. One of the key risks is that retail investors often build systems that deliver near-flawless results on historical data but lose stability in real time. Such a problem arises when the model becomes overly fitted to past market conditions and captures accidental dependencies. Finance-related cross-validation, such as Combinatorial Purged Cross-Validation, can be used to avoid this problem by testing the model performance and lowering the risk of claiming reliability from spurious results.

The second major problem is the difference between the backtest and the actual trade being executed. In backtesting, it is assumed that all trades are executed perfectly, that is, instantaneously and at the closing price. In the real market environment, slippage and spreads exert a substantial influence. These factors can absorb a significant part of profit, particularly in strategies with high portfolio turnover. The resolution of this problem requires a more realistic modeling of trading conditions that includes execution costs.

A separate barrier is that even the presence of a system does not yet ensure its consistent observance. After entering a position, the investor may commit emotional errors that undermine the strategy's logic. Most often, this manifests as closing profitable trades too early or delaying the exit from losing positions while waiting for a reversal. The path toward resolving this problem consists of strict adherence to predefined rules and reducing the space for subjective decisions at the moment of action. The higher the discipline of execution, the greater the likelihood that the quantitative approach will retain its effectiveness beyond the theoretical model.

4. Conclusion

The conducted analysis shows that the transition of retail investing to an institutional logic represents a change in the very model of decision-making. At the center of this change lies the shift from reaction to noise, media impulse, and situational judgment to regime diagnostics, quantitative filtration, and execution discipline. The IDW-RQI concept integrates these elements into a unified framework, in which each trade undergoes sequential verification based on market conditions, trend structure, expressed through SMA formations and PPM readings, and the historical durability of the signal ER.

The obtained results confirm the applied validity of the proposed approach. A systematic portfolio based on data for 2015–2025 demonstrated higher returns, lower volatility, shallower drawdowns, and a higher overall efficiency ratio than a passive allocation to a broad index. The meaning of this advantage lies in selective participation across market phases and in avoiding exposure when the probability of error increases.

The article's theoretical value lies in its consideration of retail investing through the prism of the institutional contours of capital management. Behavioral distortions, the gamification of the brokerage environment, herd reactions, and signal overload are systemic sources of risk that require formalized limitations. Within this framework, behavioral control becomes a necessary element of the investment process and is incorporated into the strategy's architecture.

The prospects for further development of this approach include increased model resilience to shifts in market regimes, the inclusion of execution costs, and stricter signal verification outside the training sample. The article argues that mature retail investing takes shape where decision-making is subordinated to procedure and capital is managed through a reproducible set of rules. This logic brings the private investor closer to institutional practice and establishes the basis for more resilient work in the contemporary market.

References

Chapkovski, P., Khapko, M., & Zoican, M. (2024). Trading Gamification and Investor Behavior. *Management Science*, *72*(1), 32–56. https://doi.org/10.1287/mnsc.2022.02650

Chen, Y., Li, S. Z., Tang, Y., & Zhou, G. (2025). Anomalies as New Hedge Fund Factors. *Journal of Financial and Quantitative Analysis*, *60*(8), 3660–3693. https://doi.org/10.1017/s0022109025101270

Eaton, G. W., Green, T. C., Roseman, B. S., & Wu, Y. (2022). Retail trader sophistication and stock market quality: Evidence from brokerage outages. *Journal of Financial Economics*, *146*(2), 502–528. https://doi.org/10.1016/j.jfineco.2022.08.002

Klepacki, J. (2025). The Fear of Missing Out (FOMO) Effect in Cryptocurrency Trading: Analyses of Mass Behavior and Its Consequences in the Era of Unpredictable Extreme Phenomena. *European Research Studies Journal*, *XXVIII* (Issue 2), 938–949. https://doi.org/10.35808/ersj/4019

Li, T., Chen, H., Liu, W., Yu, G., & Yu, Y. (2023). Understanding the role of social media sentiment in identifying irrational herding behavior in the stock market. *International Review of Economics & Finance*, *87*, 163–179. https://doi.org/10.1016/j.iref.2023.04.016

Luo, P., Ravina, E., Sammon, M., & Viceira, L. (2025). Retail Investors' Contrarian Behavior Around News, Attention, and the Momentum Effect. *National Bureau of Economic Research*. https://doi.org/10.3386/w34086

Poudel, P., & Paudel, S. (2025). Quantitative Trading Strategy, Backtesting, and Performance Analysis Using Python: A Data-Driven Analysis. *Quest Journal of Management and Social Sciences*, *7*(2), 219–238. https://doi.org/10.3126/qjmss.v7i2.87782

Tudor, C., & Sova, R. (2022). Flexible Decision Support System for Algorithmic Trading: Empirical Application on Crude Oil Markets. *IEEE Access*, *10*, 9628–9644. https://doi.org/10.1109/access.2022.3143767

Warkulat, S., & Pelster, M. (2024). Social media attention and retail investor behavior: Evidence from r/wallstreetbets. *International Review of Financial Analysis*, *96*, 103721. https://doi.org/10.1016/j.irfa.2024.103721