Volume-Weighted Golden Ratio Estimator (vGRE) for Drawdown and Tail-Risk Control for Wealth Portfolios

Lanz CWJ Chan

Finamatrix Quant-Lab, Singapore

Email: lanz@finamatrix.net

Wing-Keung Wong

Department of Finance, Quantum AI Research Center, Fintech & Blockchain Research Center, and Big Data Research Center, Asia University, Taiwan

Department of Medical Research, China Medical University Hospital, Taiwan

Business, Economic and Public Policy Research Centre, Hong Kong Shue Yan University

The Economic Growth Centre, Nanyang Technological University, Singapore

***Corresponding author* Email**: wong@asia.edu.tw

Published on March 12, 2026

Abstract

Purpose. This paper introduces the Volume-Weighted Golden Ratio Estimator (vGRE) as a transparent, cybernetic overlay for dynamic drawdown and tail-risk control in wealth management portfolios, addressing limitations of traditional volatility- and VaR-based risk metrics that fail to protect high-net-worth and ultra-high-net-worth investors against sharp drawdowns and tail events.

Design/methodology/approach. The framework integrates golden-ratio-based segmentation of price swings with genetic optimization and volume-weighted confirmation to distinguish meaningful market moves from technical noise. Using 5-minute NAS100 index data from January 2024 to January 2026, we compare a systematic vGRE-based strategy against standard VWAP, RSI, Bollinger Bands, and a buy-and-hold benchmark through comprehensive backtesting and walk-forward validation.

Findings. The vGRE overlay achieves a Sharpe ratio of 2.34 compared with 1.76 for VWAP and 1.28 for buy-and-hold, while reducing maximum drawdown to 8.2% versus 14.5% and 22.7%, respectively. The system generates early warning signals 2–4 days ahead of the three largest drawdown episodes in the sample and reduces false-positive trading signals by 51% relative to an unweighted variant.

Practical implications. The vGRE framework offers wealth managers, family offices, and private banks a practical, implementable risk overlay that can sit atop existing strategic allocations, enhancing downside protection without requiring wholesale redesign of investment processes. The modular design enables integration into tactical risk budgeting, derivative hedging triggers, and investment committee decision protocols.

Originality/value. This study demonstrates that volume-weighted, cybernetic risk overlays combining golden-ratio structures with evolutionary optimization can materially improve drawdown control and tail-risk detection without requiring complex predictive models or black-box machine learning. The vGRE framework provides a theoretically grounded yet operationally accessible approach to adaptive risk management for private wealth portfolios.

Keywords: Wealth management; Drawdown control; Tail-risk; Volume-weighted indicators; Golden ratio; Risk cybernetics; Algorithmic overlay

JEL Classification: G11, G17, G32, C44, C61, D81

1 Introduction

The management of large taxable portfolios for high-net-worth individuals (HNWIs), ultra-high-net-worth (UHNW) families, and family offices requires risk frameworks that prioritize capital preservation and the avoidance of severe drawdowns. Conventional risk tools built around historical volatility and Value-at-Risk (VaR) often underestimate losses in stressed markets and adapt too slowly to regime shifts, exposing private wealth portfolios to abrupt capital erosion and forced de-risking at inopportune times (Guo et al., 2019; Hull, 2018; Ma & Wong, 2010; McNeil et al., 2015). At the same time, the proliferation of algorithmic trading and crowding around popular technical indicators has made market dynamics more path-dependent and behaviorally driven, complicating the task of designing robust, real-time risk overlays for wealth management mandates (Cont, 2017; Danielsson et al., 2016).

Traditional portfolio optimization, even when extended to higher moments and downside-risk measures, typically assumes relatively stable risk-return relationships and relies on static parameters calibrated over long samples (Bai et al., 2016; Bian et al., 2013). In practice, wealth managers and family offices face heterogeneous objectives across generations, binding drawdown constraints, and episodic liquidity shocks. These features demand adaptive tools that can react to evolving market microstructure while remaining sufficiently transparent to satisfy investment committees, risk officers, and regulators. Technical indicators such as moving averages, RSI, and Bollinger Bands are widely used in practice, yet they often suffer from self-fulfilling dynamics: as adoption rises, their standalone predictive content decays, and false signals proliferate, especially in low-volume environments (Grossman & Stiglitz, 1980; Lo & MacKinlay, 1999).

This paper introduces the Volume-Weighted Golden Ratio Estimator (vGRE) as a cybernetic risk overlay designed to address these challenges in a wealth management context. The approach combines three elements. First, price action is segmented using golden-ratio-based structures, capturing self-similar swing behavior that practitioners already exploit through Fibonacci retracements (Livio, 2002). Second, a genetic optimization engine continuously adjusts segmentation parameters, allowing the system to track regime changes without relying on rigid, pre-set lookback windows (Chan & Wong, 2012, 2013). Third, the resulting golden-ratio signal is scaled by a volume ratio, so that only moves supported by abnormal trading activity generate strong risk signals (Berkowitz et al., 1988). Together, these components yield a volume-confirmed indicator that can be integrated into portfolio-level control rules for adjusting exposure, tightening risk budgets, and triggering drawdown-protection protocols.

We validate the vGRE framework on NAS100 (Nasdaq-100) index data sampled at 5-minute frequency from January 2024 to January 2026, comparing a rules-based vGRE strategy with benchmark approaches including standard VWAP, RSI, Bollinger Bands, and a buy-and-hold allocation. The vGRE overlay delivers higher risk-adjusted performance and materially lower maximum drawdowns, while providing early-warning tail-risk signals several days before major market corrections. For wealth managers, this translates into a practical, implementable overlay that can sit atop existing strategic allocations, enhancing downside protection without requiring a wholesale redesign of the investment process.

The remainder of the paper proceeds as follows. Section 2 reviews literature on risk optimization for wealth portfolios, technical analysis, and cybernetic control systems. Section 3 presents the theoretical foundation and mathematical formulation of the vGRE framework. Section 4 describes empirical validation using NAS100 data. Section 5 discusses practical implementation for wealth management platforms. Section 6 concludes with implications and future research directions.

2 Literature Review

2.1 Risk Optimization for Wealth Portfolios

Risk quantification and portfolio optimization remain central challenges for wealth managers serving HNWIs and family offices (Hull, 2018; McNeil et al., 2015). Traditional mean-variance optimization suffers from severe estimation error, particularly when the dimension-to-sample-size ratio is large, causing plug-in estimates to overstate theoretical optimal returns (Bai et al., 2009a, 2009b; Leung et al., 2012; Li et al., 2018; Meucci, 2005; Ortobelli Lozza et al., 2018). For taxable wealth portfolios with multi-generational horizons and strict drawdown constraints, these estimation issues are compounded by time-varying volatility, fat-tailed return distributions, and regime shifts (Bianchi et al., 2021; Guidolin & Timmermann, 2007; Hui et al., 2024; Li, Bai, et al., 2022; Li, Hui, et al., 2025; Li, Jiang, et al., 2022; Li, Li, et al., 2018; Lv et al., 2021; Wong, Zhu, et al., 2025).

Higher-moment risk measures—co-skewness and co-kurtosis—significantly enhance portfolio models by capturing asymmetric tail risk and investor demands for downside protection (Liow & Chan, 2005). Stochastic dominance (SD) approaches offer powerful frameworks for comparing investment alternatives without restrictive distributional assumptions (Wong, 2007; Wong et al., 2008). Wong (2007) extended traditional mean-variance analysis to accommodate both risk-averse and risk-seeking preferences, while Wong et al. (2008) applied stochastic dominance to hedge fund evaluation, showing superior filtering capabilities relative to CAPM and mean-variance methods for non-normal distributions.

The SD approach has been applied across diverse markets—including momentum strategies, REITs and funds, exchange-traded funds, commodity and property portfolios—illustrating its flexibility for non-normal return distributions (Chiang et al., 2008; Fong et al., 2005; Gasbarro et al., 2012; Hoang et al., 2015a, 2015b; Lean et al., 2010, 2015; Lv et al., 2023). In addition, Wong and Li (1999), Li and Wong (1999), Wong and Chan (2008), Egozcue et al. (2011), Ma and Wong (2010), Guo and Wong (2016), Guo et al. (2017a, 2017b, 2019), Chan et al. (2020, 2022), Wong et al. (2023, 2025), etc. have been developing some new theoretical results for SD. Recently, Lv et al. (2021) discovered that including the highest mean and the smallest variance assets in the portfolio yields better returns, and Wong et al. (2026) further showed that including the highest mean and the smallest variance assets could get arbitrage opportunities from no-arbitrage portfolios.

Recent advances in data-driven decision-making emphasize direct optimization from data to prescriptions, bypassing intermediate prediction phases (Bertsimas et al., 2022; Elmachtoub & Grigas, 2022). Tree-based and model-free optimization methods enable heterogeneous portfolio strategies that adapt to client-specific constraints and preferences (Bertsimas et al., 2021; Mišić, 2020). For wealth management, these developments suggest that adaptive, real-time risk overlays can improve capital preservation outcomes without relying on complex forecasting models.

2.2 Volume-Weighted Technical Analysis and Self-Fulfilling Dynamics

Technical analysis—price patterns, momentum indicators, and chart formations—has long been used by practitioners despite academic skepticism rooted in efficient market theory (Brock et al., 1992; Fama, 1970). Behavioral finance research demonstrates that technical indicators influence collective trading behavior, creating feedback loops that partially validate signals but also introduce instability as adoption spreads (Kahneman & Tversky, 1979; Shiller, 2003). The self-fulfilling prophecy problem arises when widespread use of technical rules generates the patterns that those rules predict, eroding their effectiveness over time (Black, 1986; Grossman & Stiglitz, 1980).

Volume analysis provides crucial information about the strength and sustainability of price movements (Campbell et al., 1993; Karpoff, 1987). Volume-weighted average price (VWAP) serves as a standard execution benchmark for institutional trading, while volume profile analysis identifies price levels with concentrated activity (Berkowitz et al., 1988). Volume-weighted approaches partially mitigate self-fulfilling issues by requiring actual transaction confirmation rather than relying solely on price-based signals (Easley et al., 2012). Recent behavioral finance literature documents systematic deviations, including overconfidence, representativeness heuristics, and momentum-contrarian patterns (Fabozzi et al., 2013; Guo et al., 2017a, 2017b; Lam et al., 2010, 2012; Wong et al., 2018), which create exploitable opportunities for adaptive systems that continuously recalibrate to changing market psychology.

2.3 Cybernetic Control and Adaptive Optimization

Cybernetics—the study of control and communication in complex systems—offers frameworks for financial risk management through feedback-driven adaptation (Ashby, 1956; Wiener, 1948). Control theory applications in finance include optimal portfolio rebalancing, liquidity management, and algorithmic execution (Gârleanu & Pedersen, 2013; Merton, 1971). Cybernetic systems continuously monitor state variables, compare them against target objectives, and implement corrective actions through feedback loops.

Genetic algorithms have demonstrated superior performance for non-convex, multi-modal financial optimization problems where traditional gradient methods fail (Goldberg, 1989; Holland, 1992). Chan and Wong (2012, 2013) pioneered genetic-algorithm architectures for risk-cybernetics in FX and high-frequency trading, establishing that evolutionary optimization achieves superior risk-adjusted returns through continuous adaptive parameter selection. Building on this foundation, vGRE extends risk-cybernetics in three directions. First, it tailors the architecture to wealth management mandates with explicit drawdown and tail-risk constraints rather than speculative trading objectives. Second, it integrates golden-ratio segmentation with volume-weighted confirmation to reduce self-fulfilling technical signals and improve tail-event detection. Third, it embeds the overlay into portfolio-level control rules and governance processes suitable for family offices and private banks.

3 Theoretical Framework

3.1 Conceptual Foundation

The vGRE framework rests on three theoretical pillars: golden ratio segmentation, volume-weighted analysis, and cybernetic feedback. We formalize these concepts through a unified mathematical structure enabling computational implementation.

3.2 Golden Ratio Segmentation

The golden ratio $\phi = \frac{1+\sqrt{5}}{2} \approx 1.618$ exhibits unique mathematical properties relevant to optimization and natural systems (Livio, 2002). In financial contexts, golden ratio retracements identify potential support and resistance levels based on self-similar fractal market structures observed by practitioners.

Let P_t denote asset price at time t, and define a price swing from local minimum P_{min} to local maximum P_{max}. Golden ratio retracement levels are:

$$R_k = P_{max} - \left(\frac{1}{\phi^k}\right)(P_{max} - P_{min}), k = 1,2,3, \dots \tag{1}$$

These levels partition the price range according to golden ratio proportions: $\frac{1}{\phi} \approx 0.618$, $\frac{1}{\phi^2} \approx 0.382$, $\frac{1}{\phi^3} \approx 0.236$.

3.3 Volume-Weighted Analysis

Volume provides critical information about conviction behind price movements. Let V_t represent trading volume at time t. The volume-weighted average price (VWAP) for period $[t_0, t_1]$ is:

$$VWAP_{[t_0,t_1]} = \frac{\sum_{t=t_0}^{t_1} P_t \cdot V_t}{\sum_{t=t_0}^{t_1} V_t} \tag{2}$$

Volume-weighted metrics filter noise by emphasizing price levels with substantial transaction activity, reducing sensitivity to low-volume spikes that may reflect temporary liquidity imbalances rather than fundamental reassessments (Berkowitz et al., 1988; Campbell et al., 1993).

3.4 Cybernetic Control Architecture

A cybernetic system comprises four essential components: (i) sensor—monitors price, volume, and volatility; (ii) comparator—evaluates current state against target objectives and risk limits; (iii) controller—determines optimal control actions based on error signals; (iv) actuator—implements control actions through position adjustments (Ashby, 1956; Wiener, 1948).

The feedback loop operates continuously: State → Measurement → Error → Control → Action → State. Let x_t represent the system state vector, u_t the control action, and r_t the target reference. The error signal is $e_t = r_t - x_t$, and the control law determines $u_t = f(e_t, e_{t-1}, \dots, e_{t-k})$.

3.5 vGRE Mathematical Formulation

The Volume-Weighted Golden Ratio Estimator integrates these theoretical components into a unified framework.

Golden Ratio Function (GRF). Define:

$$GRF_t(a_t, b_t) = \frac{a_t + b_t}{max(a_t, b_t)}, \tag{3}$$

where a_t and b_t are price segment lengths derived from recent price action. To approximate the golden ratio, we require $\frac{GRF_t(a_t,b_t)}{\phi} \approx 1$.

Genetic Optimization. Parameters a_t and b_t are optimized through a genetic algorithm, minimizing:

$$J_{opt} = \min_{a_t, b_t} \left| \frac{GRF_t(a_t, b_t)}{\phi} - 1 \right| + \lambda \cdot Var(a_t, b_t), \tag{4}$$

where the penalty term $\lambda \cdot Var(a_t, b_t)$ ensures stability by discouraging excessive parameter volatility. The genetic algorithm employs standard evolutionary operations—initialization, selection, crossover, mutation, and replacement—to explore the parameter space efficiently without requiring differentiability or convexity (Chan & Wong, 2012; Holland, 1992).

Golden Ratio Estimator (GRE). The normalized metric is:

$$GRE_t = \frac{GRF_t(a_t, b_t)}{\phi}. \tag{5}$$

Values near 1.0 indicate strong golden ratio alignment, suggesting potential reversal points.

Volume-Weighted Golden Ratio Estimator (vGRE). The final vGRE adjusts GRE by volume weighting:

$$vGRE_t = \alpha \cdot GRE_t \cdot \frac{V_t}{V^{-}_{[t-n,t]}}, \tag{6}$$

where α is a scaling constant, V_t is current period volume, and $V^{-}_{[t-n,t]}$ is moving average volume over lookback period n. The volume ratio amplifies signals during high-volume periods (strong conviction) and dampens them during low-volume periods (potential noise).

Interpretation Framework. The vGRE signal is interpreted as follows:

Table 1: vGRE signal interpretation for portfolio risk adjustments

vGRE Signal	Interpretation
Spike (rapid increase)	Potential downside risk; reduce exposure
Dip (rapid decrease)	Potential upside opportunity; increase exposure
Stable range	Neutral; maintain current positions
Divergence from price	Weakening trend; prepare for reversal

3.6 Dynamic Thresholds and Position Sizing

Static thresholds suffer from changing volatility regimes. We implement adaptive thresholds based on rolling statistics:

$$Threshold_{upper}(t) = \mu_{vGRE}(t) + \beta \cdot \sigma_{vGRE}(t), \tag{7}$$

$$Threshold_{lower}(t) = \mu_{vGRE}(t) - \beta \cdot \sigma_{vGRE}(t), \tag{8}$$

where $\mu_{vGRE}(t)$ and $\sigma_{vGRE}(t)$ are rolling mean and standard deviation, and β is a sensitivity parameter.

When vGRE crosses dynamic thresholds, the control system determines position adjustments. Position sizing is proportional to signal strength and inversely proportional to portfolio risk:

$$Position\ Size_t = \kappa \cdot \frac{|vGRE_t - \mu_{vGRE}(t)|}{\sigma_{vGRE}(t)} \cdot \frac{1}{Portfolio\ VaR_t}, \tag{9}$$

where κ scales maximum position size to respect overall risk budgets typical in wealth mandates.

3.7 Tail-Risk Detection

Traditional VaR estimates normal loss distributions but underestimates tail-risk during market stress. The vGRE framework enhances tail-risk detection through volume-weighted early warning signals. We model the tail distribution of vGRE using the Generalized Pareto Distribution (GPD):

$$F(x) = 1 - \left(1 + \frac{\xi(x - \mu)}{\sigma}\right)^{-\frac{1}{\xi}}, \tag{10}$$

where ξ is the shape parameter, μ the location, and σ the scale. Positive ξ indicates heavy tails susceptible to extreme events. The tail-risk threshold is defined as the α-quantile:

$$vGRE_{tail} = GPD^{-1}(1 - \alpha). \tag{11}$$

When $vGRE_t > vGRE_{tail}$ and volume exceeds a threshold γ, the system triggers enhanced risk protocols including position reduction, hedging activation, or capital reallocation to lower-beta assets—actions directly relevant to family-office risk governance.

4 Empirical Validation

This section describes the data, benchmark strategies, and performance metrics used to evaluate vGRE on NAS100.

4.1 Data and Methodology

We validate the vGRE framework using NAS100 (Nasdaq-100 Index) data from January 2024 through January 2026, encompassing diverse market conditions, including trending periods, range-bound consolidations, and volatility spikes. The NAS100 represents a typical equity sleeve in UHNW portfolios with substantial technology and growth exposure.

Table 2: Dataset characteristics for empirical validation

Characteristic	Value
Asset	NAS100 Index (Nasdaq-100)
Period	January 1, 2024–January 31, 2026
Frequency	5-minute bars
Total observations	105,120
Training period	Jan 2024–June 2025 (70%)
Testing period	July 2025–Jan 2026 (30%)

Data preprocessing includes removal of after-hours trading with insufficient liquidity, outlier detection using inter-quartile range methods, forward-filling for missing volume observations, and adjustment for index rebalancing events.

4.2 Benchmark Comparisons

We compare vGRE performance against established risk metrics and technical indicators: (i) VaR (Value-at-Risk) using historical simulation with 95% confidence; (ii) CVaR (Conditional VaR) for expected shortfall; (iii) GARCH volatility; (iv) RSI (Relative Strength Index); (v) Bollinger Bands; (vi) Standard VWAP without golden ratio optimization.

4.3 Trading Strategy Implementation

We implement a systematic strategy based on vGRE signals with the following rules:

1. Long entry when $vGRE_t < Threshold_{lower}(t)$,
2. Short entry when $vGRE_t > Threshold_{upper}(t)$,

3. Position sizing proportional to signal strength,
4. Stop-loss at 2% adverse movement, and
5. Take-profit at 3% favorable movement.

Performance evaluation employs standard wealth-management metrics: Sharpe ratio (risk-adjusted return), maximum drawdown (largest peak-to-trough decline), Calmar ratio (return divided by maximum drawdown), win rate, and profit factor.

4.4 Results: Risk-Adjusted Performance

Table 3: Comparative performance metrics across strategies (testing period)

Strategy	Sharpe	Max DD	Win Rate	Profit Factor	Calmar
vGRE Framework	2.34	−8.2%	64.3%	1.85	2.85
Standard VWAP	1.76	−14.5%	58.1%	1.35	1.21
RSI Strategy	1.52	−16.8%	55.7%	1.22	0.90
Bollinger Bands	1.63	−15.2%	56.9%	1.28	1.02
Buy-and-Hold	1.28	−22.7%	N/A	1.10	0.56

The vGRE framework achieves superior risk-adjusted returns with substantially lower maximum drawdown compared to all benchmarks. The 33% improvement in Sharpe ratio over standard VWAP and the 64% reduction in maximum drawdown relative to buy-and-hold demonstrate the value of genetic optimization and volume-weighted confirmation. For wealth managers, the Calmar ratio of 2.85 indicates robust performance per unit of tail risk—a critical metric for clients with strict drawdown mandates.

4.5 Results: Tail-Risk Detection

We evaluate tail-risk detection capability by examining performance during the three largest drawdown events in the testing period.

Table 4: Tail-risk detection during major drawdown events

Event	Date	Index Drawdown	vGRE Early Warning
Event 1	Aug 2025	−12.3%	3 days prior
Event 2	Oct 2025	−9.7%	2 days prior

Event 3	Jan 2026	−11.5%	4 days prior

The vGRE system provided advanced warning for all three significant market corrections, enabling proactive risk reduction. In contrast, traditional VaR models flagged risk only after drawdowns commenced. For family offices and private banks, this early-warning capability translates into operational time to adjust portfolio exposures, communicate with clients, and execute hedging strategies before capital erosion accelerates.

4.6 Results: Volume Confirmation Impact

We analyze the impact of volume-weighting on signal quality by comparing vGRE against an unweighted GRE variant.

Table 5: Volume confirmation analysis: signal quality comparison

Metric	vGRE (Volume-Weighted)	GRE (Unweighted)
Total Signals	342	518
True Positives	220	267
False Positives	122	251
Precision	64.3%	51.5%

Volume-weighting reduces false positives by 51% compared to the unweighted variant, confirming that transaction volume provides essential validation. For wealth managers, higher precision translates into lower turnover, reduced transaction costs, and fewer disruptive position changes that can trigger tax events in taxable portfolios.

4.7 Robustness Analysis

The vGRE framework addresses overfitting through design constraints and rigorous evaluation. The genetic algorithm operates over a compact, economically motivated parameter space, limiting flexibility to fit noise. We implement rolling walk-forward validation: parameters optimized on a calibration window are applied only to subsequent, non-overlapping test windows, ensuring performance metrics reflect genuinely unseen data.

Bootstrap-based performance estimation generates 1,000 resampled return paths to compute empirical distributions of Sharpe ratio, maximum drawdown, and profit factor. The vGRE strategy's observed Sharpe ratio of 2.34 lies within the body of its bootstrap distribution, and the 95% confidence interval for Sharpe improvement over VWAP remains strictly positive. These results are consistent with deflated-Sharpe corrections accounting for parameter uncertainty and selection effects, suggesting documented performance is robust rather than an artifact of data mining.

Transaction cost sensitivity analysis confirms that vGRE performance remains superior even when assuming 5 basis points per trade, typical for institutional equity execution. Parameter sensitivity tests show stable performance across reasonable ranges of β (threshold sensitivity) and κ (position-sizing scale), indicating the framework is not over-tuned to specific calibration choices.

Taken together, the magnitudes of the reported performance improvements are economically plausible and consistent with the vGRE design. In particular, a reduction in maximum drawdown from 22.7% (buy-and-hold) to 8.2% (vGRE) on a single NAS100 sleeve, combined with a Sharpe ratio of 2.34, is in line with what an actively managed, intraday risk overlay can achieve on a volatile growth index over a relatively short evaluation window. Likewise, the observed 51% reduction in false-positive signals relative to the unweighted variant reflects the intended role of volume confirmation in filtering out low-conviction moves rather than a “free lunch” generated by overfitting.

At the same time, the subsequent Limitations section clarifies that these results are obtained on a single, highly liquid index over a specific intraday sample with stylized execution assumptions, so they should be interpreted as evidence of potential rather than guaranteed outperformance across all markets and implementations.

Finally, we note that the vGRE framework is optimisation-driven and does not rely on linear time-series regressions, which reduces exposure to the spurious-regression and mixed-order integration pitfalls documented in recent econometric studies (Cheng et al., 2022; Wong, Cheng, & Yue, 2024; Wong & Pham, 2022a, 2022b, 2023a, 2023b, 2025a, 2025b, 2026a, 2026b; Wong, Pham, & Yue, 2024; Wong & Yue, 2024).

4.8 Wealth Management Illustration

To illustrate practical application, consider a family office managing a $50 million portfolio with 60% equities (including a $10 million NAS100 sleeve) and 40% fixed income. The investment committee mandates a maximum portfolio drawdown of 15% and requires advance warning protocols for tail-risk events.

Applying the vGRE overlay to the NAS100 sleeve over the testing period, the maximum drawdown of that sleeve falls from 22.7% (buy-and-hold) to 8.2% (vGRE), reducing portfolio-level drawdown exposure by approximately 4.5 percentage points (accounting for correlation with other portfolio components). Early-warning signals 2–4 days before major corrections provide the investment committee with actionable lead time to rebalance, add hedges, or reduce beta through derivatives overlays.

From a client-experience perspective, smoother equity returns reduce the likelihood of emotionally driven asset allocation changes and forced de-risking at market troughs. For taxable portfolios, the vGRE overlay's higher win rate and lower turnover (342 signals vs 518 for unweighted variants) mitigate tax friction and preserve after-tax wealth accumulation.

5 Implementation for Wealth Platforms

This section explains how vGRE can be integrated into existing wealth-management platforms and governance structures.

5.1 Integration into Existing Portfolios

The vGRE framework is designed as a modular risk overlay compatible with existing discretionary and systematic mandates. Wealth managers can integrate vGRE signals into investment processes at multiple levels:

1. **Tactical risk budgeting**: Use vGRE thresholds to adjust portfolio beta dynamically, scaling equity exposure between strategic minimum and maximum bands based on tail-risk signals.

2. **Derivative overlays**: Trigger options-based hedging (protective puts, collars) when vGRE crosses tail-risk thresholds, preserving upside participation while capping downside.

3. **Asset allocation committees**: Present vGRE signals alongside traditional VaR and volatility metrics to inform discretionary rebalancing decisions and risk-appetite discussions.

4. **Client reporting**: Display vGRE time series and threshold breaches in risk dashboards, enhancing transparency and client understanding of proactive risk management.

5.2 Computational Infrastructure

The vGRE system operates efficiently on standard institutional infrastructure. Key implementation components include:

1. **Data ingestion**: Connect to market data feeds (Bloomberg, Refinitiv, exchange APIs) with 1–5 minute refresh frequencies.

2. **Genetic optimization engine**: Parallel processing across multiple cores accelerates convergence; typical cycle time is sub-100 milliseconds on 8-core hardware.

3. **Risk monitoring dashboard**: Real-time visualization of vGRE signals, dynamic thresholds, portfolio positions, and alert history.

4. **Execution integration**: Interface with order management systems (OMS) and execution management systems (EMS) for automated or semi-automated position adjustments.

Benchmark testing confirms that the vGRE calculation cycle, including genetic optimization, completes within 100 milliseconds on standard hardware (8-core CPU, 32GB RAM), enabling real-time applications even for high-frequency rebalancing strategies.

5.3 Regulatory and Governance Considerations

Financial institutions operate under stringent regulatory frameworks requiring model validation, stress testing, and documentation. The vGRE framework supports regulatory compliance through:

1. **Model validation**: Backtesting on historical data across multiple regimes, out-of-sample evaluation, sensitivity analysis, and comparison against benchmark models.

2. **Stress testing**: Evaluation under adverse scenarios (market crashes, liquidity crises, volatility spikes, flash crashes) to assess system robustness.

3. **Audit trail**: Complete documentation of mathematical specifications, implementation code, parameter selection rationale, and performance monitoring reports.

4. **Transparency**: The vGRE formulation is interpretable and explainable to investment committees, risk officers, and regulators, contrasting favorably with black-box machine learning approaches.

For wealth managers subject to fiduciary standards and suitability requirements, vGRE's transparent structure and clear risk-reduction objectives facilitate compliance with regulatory oversight and client-disclosure obligations.

5.4 Comparison with Alternative Approaches

The vGRE framework offers distinct advantages relative to alternative risk-management tools:

Versus traditional VaR: VaR assumes normal or parametric distributions and provides no early-warning capability. vGRE incorporates volume-weighted signals and extreme value theory for superior tail-risk detection with advance lead time.

Versus machine learning models: Deep learning and ensemble methods often achieve high in-sample accuracy but lack transparency and interpretability. vGRE combines genetic optimization with economically motivated structure (golden ratio, volume weighting), enabling explainability critical for wealth management governance.

Versus static technical indicators: RSI, Bollinger Bands, and moving averages use fixed parameters and lack adaptive feedback. vGRE continuously recalibrates through genetic optimization and volume confirmation, reducing false signals and improving robustness across regimes.

6 Conclusion

This paper introduces the Volume-Weighted Golden Ratio Estimator (vGRE) as a cybernetic risk overlay for dynamic drawdown and tail-risk control in wealth management portfolios. By integrating golden-ratio segmentation, genetic optimization, and volume-weighted confirmation, the vGRE framework addresses key limitations of traditional volatility- and VaR-based risk metrics: static parameters that fail to adapt to regime changes, inadequate tail-risk capture during market stress, and high false-positive rates in technical indicators.

Empirical validation on NAS100 index data from January 2024 to January 2026 shows that a systematic vGRE strategy delivers higher risk-adjusted returns and substantially lower maximum drawdowns than VWAP, RSI, Bollinger Bands, and buy-and-hold, while providing early-warning signals several days before major corrections and reducing false positives through volume confirmation. For wealth managers and family offices, this translates into a practical overlay that improves drawdown control and tail-risk management without requiring wholesale changes to existing strategic allocations.

6.1 Theoretical and Practical Implications

The vGRE framework contributes to wealth management literature by demonstrating that volume-weighted, cybernetic risk overlays can materially improve drawdown control and tail-risk detection without requiring complex predictive models or black-box machine learning. The integration of golden-ratio structures—already familiar to practitioners through Fibonacci retracements—with evolutionary optimization and volume confirmation provides a theoretically grounded yet operationally accessible approach to adaptive risk management.

For practitioners, the key implication is that real-time, rule-based overlays can enhance client outcomes and portfolio resilience while preserving transparency and interpretability. The vGRE system's ability to generate advance warning signals enables proactive rather than reactive risk management, a critical distinction for clients with strict drawdown mandates and multi-generational investment horizons.

Unlike black-box predictive models whose value depends heavily on backtest performance, vGRE is designed as a rule-based risk overlay whose core behaviour is determined by transparent optimisation and volume-confirmed thresholds rather than statistical forecasting accuracy.

In wealth-management settings, this shifts the role of empirical backtests from certifying a fragile return forecast to validating that the overlay reliably reshapes drawdown and tail-risk profiles across different regimes and reasonable parameter choices.

6.2 Limitations

Despite these encouraging results, several limitations of our analysis merit emphasis. The empirical analysis focuses on a single, highly liquid equity index (NAS100) using 5-minute data between January 2024 and January 2026, which may limit generalisability to less liquid markets, alternative asset classes, or different sampling frequencies. Execution is modelled with stylised transaction costs and does not capture market impact or microstructure frictions that large institutional trades may face. In addition, the genetic-optimisation layer assumes access to reliable intraday data and institutional-grade infrastructure, which may constrain implementation by smaller firms.

6.3 Future Research Directions

Several extensions merit investigation:

1. **Multi-asset portfolios**: Apply vGRE to diversified portfolios spanning equities, fixed income, alternatives, and real assets, evaluating performance across correlation regimes and asset-class rotations.

2. **Client risk profiles**: Integrate vGRE thresholds with client-specific risk tolerances, time horizons, and liquidity constraints to customize overlay aggressiveness.

3. **Hybrid ML-vGRE systems**: Combine vGRE signals with machine learning regime-classification models to switch between risk-on and risk-off parameter sets.

4. **ESG integration**: Extend vGRE to incorporate environmental, social, and governance factors, using ESG-screened universes and sustainability-linked position-sizing rules.

5. **Tax optimization**: Develop tax-aware vGRE variants that account for capital gains realization, loss harvesting, and holding-period considerations in taxable wealth portfolios.

Future research can integrate vGRE with complementary strands such as herding behaviour (Batmunkh et al., 2018, 2020; Choijil et al., 2022; Vieito et al., 2024), technical analysis (Chan et al., 2014; Kung & Wong, 2009a, 2009b; Lam et al., 2007; Wong et al., 2001, 2003, 2005; Wong & McAleer, 2009), and portfolio strategy design (Lu et al., 2018, 2021, 2022), while using optimisation-driven methods that avoid or explicitly correct for spurious-regression effects documented in recent work (Cheng et al., 2022; Wong, Cheng, & Yue, 2024; Wong & Pham, 2022a, 2022b, 2023a, 2023b, 2025a, 2025b, 2026a, 2026b; Wong, Pham, & Yue, 2024; Wong & Yue, 2024).

References

Ashby, W. R. (1956). *An introduction to cybernetics*. Chapman & Hall.

Bai, Z., Liu, H., & Wong, W. K. (2009a). Enhancement of the applicability of Markowitz's portfolio optimization by utilizing random matrix theory. *Mathematical Finance*, *19*(4), 639–667. https://doi.org/10.1111/j.1467-9965.2009.00383.x

Bai, Z., Liu, H., & Wong, W. K. (2009b). On the Markowitz mean-variance analysis of self-financing portfolios. *Risk and Decision Analysis*, *1*(1), 35–42. https://doi.org/10.3233/RDA-2009-0003

Bai, Z., Liu, H., & Wong, W. K. (2016). Making Markowitz's portfolio optimization theory practically useful. *SSRN Electronic Journal*, Article 2881866. https://doi.org/10.2139/ssrn.2881866

Batmunkh, M.-U., Choijil, E., Vieito, J. P., Espinosa-Méndez, C., & Wong, W. K. (2020). Does herding behavior exist in the Mongolian stock market? *Pacific-Basin Finance Journal*, *62*, Article 101352. https://doi.org/10.1016/j.pacfin.2020.101352

Batmunkh, M.-U., McAleer, M., Moslehpour, M., & Wong, W. K. (2018). Confucius and herding behavior in the stock markets in China and Taiwan. *Sustainability*, *10*(12), Article 4413. https://doi.org/10.3390/su10124413

Berkowitz, S. A., Logue, D. E., & Noser, E. A. (1988). The total cost of transactions on the NYSE. *Journal of Finance*, *43*(1), 97–112. https://doi.org/10.1111/j.1540-6261.1988.tb02591.x

Bertsimas, D., Dunn, J., Mundru, N., & Pawlowski, C. (2022). Optimal prescriptive trees. *INFORMS Journal on Optimization*, *4*(2), 164–183. https://doi.org/10.1287/ijoo.2021.0065

Bertsimas, D., Orfanoudaki, A., & Wiberg, H. (2021). Interpretable clustering: An optimization approach. *Machine Learning*, *110*(1), 89–138. https://doi.org/10.1007/s10994-020-05896-2

Bian, G., McAleer, M., & Wong, W. K. (2013). Robust estimation and forecasting of the capital asset pricing model. *Annals of Financial Economics*, *8*(2), Article 1350007. https://doi.org/10.1142/S2010495213500073

Bianchi, D., Büchner, M., & Tamoni, A. (2021). Bond risk premiums with machine learning. *Review of Financial Studies*, *34*(2), 1046–1089. https://doi.org/10.1093/rfs/hhaa062

Black, F. (1986). Noise. *Journal of Finance*, *41*(3), 528–543. https://doi.org/10.1111/j.1540-6261.1986.tb04513.x

Brock, W., Lakonishok, J., & LeBaron, B. (1992). Simple technical trading rules and the stochastic properties of stock returns. *Journal of Finance*, *47*(5), 1731–1764. https://doi.org/10.1111/j.1540-6261.1992.tb04681.x

Campbell, J. Y., Grossman, S. J., & Wang, J. (1993). Trading volume and serial correlation in stock returns. *Quarterly Journal of Economics*, *108*(4), 905–939. https://doi.org/10.2307/2118454

Chan, L., & Wong, W. K. (2012). Automated trading with genetic-algorithm neural-network risk cybernetics: An application on FX markets. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.1687763

Chan, L., & Wong, W. K. (2013). Expert advisor based on genetic-algorithm risk-cybernetics systems. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.2346031

Chan, R. H., Chow, S. C., Guo, X., & Wong, W. K. (2022). Central moments, stochastic dominance, moment rule, and diversification with an application. *Chaos, Solitons & Fractals*, *161*, Article 112251. https://doi.org/10.1016/j.chaos.2022.112251

Chan, R. H., Clark, E., Guo, X., & Wong, W. K. (2020). New development on the third-order stochastic dominance for risk-averse and risk-seeking investors with application in risk management. *Risk Management*, *22*(2), 108–132.

Chan, R. H., Lee, S. T. H., & Wong, W. K. (2014). *Technical analysis and financial asset forecasting: From simple tools to advanced techniques*. World Scientific. https://doi.org/10.1142/9127

Cheng, Y., Hui, Y., Liu, S., & Wong, W. K. (2022). Could significant regression be treated as insignificant: An anomaly in statistics? *Communications in Statistics: Case Studies, Data Analysis and Applications*, *8*(1), 133–151. https://doi.org/10.1080/23737484.2022.2050755

Chiang, T. C., Lean, H. H., & Wong, W. K. (2008). Do REITs outperform stocks and fixed-income assets? New evidence from mean-variance and stochastic dominance approaches. *Journal of Risk and Financial Management*, *1*(1), 1–37. https://doi.org/10.3390/jrfm1010001

Choijil, E., Méndez, C. E., Wong, W. K., Vieito, J. P., & Batmunkh, M. U. (2022). Thirty years of herd behavior in financial markets: A bibliometric analysis. *Research in International Business and Finance*, *59*, Article 101506. https://doi.org/10.1016/j.ribaf.2021.101506

Cont, R. (2017). *Central clearing and risk transformation* (Working Paper No. 3/2017). Norges Bank.

Danielsson, J., James, K. R., Valenzuela, M., & Zer, I. (2016). Model risk of risk models. *Journal of Financial Stability*, *23*, 79–91. https://doi.org/10.1016/j.jfs.2016.02.002

Easley, D., López de Prado, M. M., & O'Hara, M. (2012). Flow toxicity and liquidity in a high-frequency world. *Review of Financial Studies*, *25*(5), 1457–1493. https://doi.org/10.1093/rfs/hhs053

Egozcue, M., Fuentes García, F., Wong, W. K., & Zitikis, R. (2011). Do investors like to diversify? A study of Markowitz preferences. *European Journal of Operational Research*, *215*(1), 188–193. https://doi.org/10.1016/j.ejor.2011.05.035

Elmachtoub, A. N., & Grigas, P. (2022). Smart "predict, then optimize." *Management Science*, *68*(1), 9–26. https://doi.org/10.1287/mnsc.2020.3922

Fabozzi, F. J., Fung, C. Y., Lam, K., & Wong, W. K. (2013). Market overreaction and underreaction: Tests of the directional and magnitude effects. *Applied Financial Economics*, *23*(18), 1469–1482. https://doi.org/10.1080/09603107.2013.829198

Fama, E. F. (1970). Efficient capital markets: A review of theory and empirical work. *Journal of Finance*, *25*(2), 383–417. https://doi.org/10.2307/2325486

Fong, W. M., Wong, W. K., & Lean, H. H. (2005). International momentum strategies: A stochastic dominance approach. *Journal of Financial Markets*, *8*(1), 89–109. https://doi.org/10.1016/j.finmar.2004.08.001

Gârleanu, N., & Pedersen, L. H. (2013). Dynamic trading with predictable returns and transaction costs. *Journal of Finance*, *68*(6), 2309–2340. https://doi.org/10.1111/jofi.12080

Gasbarro, D., Wong, W. K., & Zumwalt, J. K. (2012). Stochastic dominance and behavior towards risk: The market for iShares. *Annals of Financial Economics*, *7*(1), Article 1250005. https://doi.org/10.1142/S2010495212500054

Goldberg, D. E. (1989). Genetic algorithms in search, optimization, and machine learning. Addison-Wesley.

Grossman, S. J., & Stiglitz, J. E. (1980). On the impossibility of informationally efficient markets. *American Economic Review*, *70*(3), 393–408. https://www.jstor.org/stable/1805228

Guidolin, M., & Timmermann, A. (2007). Asset allocation under multivariate regime switching. *Journal of Economic Dynamics and Control*, *31*(11), 3503–3544. https://doi.org/10.1016/j.jedc.2006.11.006

Guo, X., Jiang, X. J., & Wong, W. K. (2017a). Stochastic dominance and omega ratio: Measures to examine market efficiency, arbitrage opportunity, and anomaly. *Economies*, *5*(4), Article 38. https://doi.org/10.3390/economies5040038

Guo, X., McAleer, M., Wong, W. K., & Zhu, L. (2017b). A Bayesian approach to excess volatility, short-term underreaction and long-term overreaction during financial crises. *The North American Journal of Economics and Finance*, *42*, 346–358.

Guo, X., Niu, C. Z., & Wong, W. K. (2019). Farinelli and Tibiletti ratio and stochastic dominance. *Risk Management*, *21*(3), 201–213. https://doi.org/10.1057/s41283-018-0041-6

Guo, X., & Wong, W. K. (2016). Multivariate stochastic dominance for risk averters and risk seekers. *RAIRO - Operations Research*, *50*(3), 575–586. https://doi.org/10.1051/ro/2015048

Hoang, T. H. V., Lean, H. H., & Wong, W. K. (2015a). Is gold good for portfolio diversification? A stochastic dominance analysis of the Paris stock exchange. *International Review of Financial Analysis*, *42*, 98–108. https://doi.org/10.1016/j.irfa.2014.11.020

Hoang, V. T. H., Wong, W. K., & Zhu, Z. Z. (2015b). Is gold different for risk-averse and risk-seeking investors? An empirical analysis of the Shanghai Gold Exchange. *Economic Modelling*, *50*, 200–211. https://doi.org/10.1016/j.econmod.2015.06.021

Holland, J. H. (1992). *Adaptation in natural and artificial systems* (2nd ed.). MIT Press.

Hui, Y., Shi, M., Wong, W. K., & Zheng, S. (2024). Pragmatic attitude to large-scale Markowitz's portfolio optimization and factor-augmented derating. *International Review of Financial Analysis*, *96*, Article 103628. https://doi.org/10.1016/j.irfa.2024.103628

Hull, J. C. (2018). Risk management and financial institutions (5th ed.). Wiley.

Kahneman, D., & Tversky, A. (1979). Prospect theory: An analysis of decision under risk. *Econometrica*, *47*(2), 263–291. https://doi.org/10.2307/1914185

Karpoff, J. M. (1987). The relation between price changes and trading volume: A survey. *Journal of Financial and Quantitative Analysis*, *22*(1), 109–126. https://doi.org/10.2307/2330874

Kung, J. J., & Wong, W. K. (2009a). Profitability of technical analysis in Singapore stock market: Before and after the Asian financial crisis. *Journal of Economic Integration*, *24*(1), 133–150. https://doi.org/10.11130/jei.2009.24.1.133

Kung, J. J., & Wong, W. K. (2009b). Efficiency of the Taiwan stock market. *Japanese Economic Review*, *60*(3), 389–394. https://doi.org/10.1111/j.1468-5876.2008.00452.x

Lam, K., Liu, T., & Wong, W. K. (2010). A pseudo-Bayesian model in financial decision making with implications to market volatility, under- and overreaction. *European Journal of Operational Research*, *203*(1), 166–175. https://doi.org/10.1016/j.ejor.2009.07.011

Lam, K., Liu, T., & Wong, W. K. (2012). A new pseudo-Bayesian model with implications for financial anomalies and investors' behavior. *Journal of Behavioral Finance*, *13*(2), 93–107. https://doi.org/10.1080/15427560.2012.683780

Lam, W. S. V., Chong, T. T. L., & Wong, W. K. (2007). Profitability of intraday and interday momentum strategies. *Applied Economics Letters*, *14*(15), 1103–1108. https://doi.org/10.1080/13504850600706925

Lean, H. H., McAleer, M., & Wong, W. K. (2010). Market efficiency of oil spot and futures: A mean-variance and stochastic dominance approach. *Energy Economics*, *32*(5), 979–986. https://doi.org/10.1016/j.eneco.2010.04.001

Lean, H. H., McAleer, M., & Wong, W. K. (2015). Preferences of risk-averse and risk-seeking investors for oil spot and futures before, during and after the Global Financial Crisis. *International Review of Economics and Finance*, *40*, 204–216. https://doi.org/10.1016/j.iref.2015.02.019

Leung, P. L., Ng, H. Y., & Wong, W. K. (2012). An improved estimation to make Markowitz's portfolio optimization theory users friendly and estimation accurate with application on the US stock market investment. *European Journal of Operational Research*, *222*(1), 85–95. https://doi.org/10.1016/j.ejor.2012.04.003

Li, C. K., & Wong, W. K. (1999). Extension of stochastic dominance theory to random variables. *RAIRO - Operations Research*, *33*(4), 509–524. https://doi.org/10.1051/ro:1999120

Li, H., Bai, Z., Wong, W. K., & McAleer, M. (2022). Spectrally-corrected estimation for high-dimensional Markowitz mean-variance optimization. *Econometrics and Statistics*, *24*, 133–150. https://doi.org/10.1016/j.ecosta.2021.02.002

Li, Z., Hui, Y., Wong, W. K., & Lin, R. (2025). Portfolio selection based on mean-generalized variance analysis: Evidence from the G20 stock markets. *Asia-Pacific Journal of Operational Research*, *42*(3), Article 2450016. https://doi.org/10.1142/S0217595924500167

Li, Z., Jiang, H., Chen, Z., & Wong, W. K. (2022). A mental account-based portfolio selection model with an application for data with smaller dimensions. *Computers & Operations Research*, *144*, Article 105801. https://doi.org/10.1016/j.cor.2022.105801

Li, Z., Li, X., Hui, Y., & Wong, W. K. (2018). Maslow portfolio selection for individuals with low financial sustainability. *Sustainability*, *10*(4), Article 1128. https://doi.org/10.3390/su10041128

Liow, K. H., & Chan, L. (2005). Higher-moment risk measures and global real estate securities. *Journal of Real Estate Portfolio Management*, *11*(2), 151–162. https://doi.org/10.1080/10835547.2005.12089717

Livio, M. (2002). The golden ratio: The story of phi, the world's most astonishing number. Broadway Books.

Lo, A. W., & MacKinlay, A. C. (1999). *A non-random walk down Wall Street*. Princeton University Press.

Lu, R., Hoang, V. T., & Wong, W. K. (2021). Do lump-sum investing strategies really outperform dollar-cost averaging strategies? *Studies in Economics and Finance*, *38*(3), 675–691. https://doi.org/10.1108/SEF-09-2020-0372

Lu, R., Wang, J.-J., & Wong, W. K. (2022). Equity investing based on size, value, momentum, and income measures in Taiwan. *Annals of Financial Economics*, *17*(4), Article 2250027. https://doi.org/10.1142/S2010495222500270

Lu, R., Yang, C. C., & Wong, W. K. (2018). Time diversification: Perspectives from the economic index of riskiness. *Annals of Financial Economics*, *13*(3), Article 1850011. https://doi.org/10.1142/S2010495218500112

Lv, Z., Tsang, C. K., Wagner, N. F., & Wong, W. K. (2023). What is an optimal allocation in Hong Kong stock, real estate, and money markets: An individual asset, efficient frontier portfolios, or a naïve portfolio? Is this a new financial anomaly? *Emerging Markets Finance and Trade*, *59*(5), 1554–1571. https://doi.org/10.1080/1540496X.2022.2146838

Lv, Z. H., Chu, A. M. Y., Wong, W. K., & Chiang, T. C. (2021). The maximum-return-and-minimum-volatility effect: Evidence from including both Health Care and Treasury-Bill in the portfolio. *Risk Management*, *23*(1), 97–122. https://doi.org/10.1057/s41283-020-00068-3

Ma, C., & Wong, W. K. (2010). Stochastic dominance and risk measure: A decision-theoretic foundation for VaR and C-VaR. *European Journal of Operational Research*, *207*(2), 927–935. https://doi.org/10.1016/j.ejor.2010.05.043

McNeil, A. J., Frey, R., & Embrechts, P. (2015). *Quantitative risk management: Concepts, techniques and tools* (Revised ed.). Princeton University Press.

Merton, R. C. (1971). Optimum consumption and portfolio rules in a continuous-time model. *Journal of Economic Theory*, *3*(4), 373–413. https://doi.org/10.1016/0022-0531(71)90038-X

Meucci, A. (2005). *Risk and asset allocation*. Springer.

Mišić, V. V. (2020). Optimization of tree ensembles. *Operations Research*, *68*(5), 1605–1624. https://doi.org/10.1287/opre.2019.1928

Ortobelli Lozza, S., Wong, W. K., Fabozzi, F. J., & Egozcue, M. (2018). Diversification versus optimality: Is there really a diversification puzzle? *Applied Economics*, *50*(43), 4671–4693. https://doi.org/10.1080/00036846.2018.1466989

Shiller, R. J. (2003). From efficient markets theory to behavioral finance. *Journal of Economic Perspectives*, *17*(1), 83–104. https://doi.org/10.1257/089533003321164967

Vieito, J. P., Espinosa, C., Wong, W. K., Batmunkh, M. U., Choijil, E., & Hussien, M. (2024). Herding behavior in integrated financial markets: The case of MILA. *International Journal of Emerging Markets*, *19*(11), 3801–3827. https://doi.org/10.1108/IJOEM-03-2022-0396

Wiener, N. (1948). Cybernetics: Or control and communication in the animal and the machine. MIT Press.

Wong, W. K. (2007). Stochastic dominance and mean-variance measures of profit and loss for business planning and investment. *European Journal of Operational Research*, *182*(2), 829–843. https://doi.org/10.1016/j.ejor.2006.09.032

Wong, W. K., & Chan, R. (2008). Markowitz and prospect stochastic dominances. *Annals of Finance*, *4*(1), 105–129. https://doi.org/10.1007/s10436-007-0072-4

Wong, W. K., Cheng, Y., & Yue, M. (2024). Could regression of stationary series be spurious? *Asia-Pacific Journal of Operational Research*, Article 2440017. https://doi.org/10.1142/S0217595924400172

Wong, W. K., Chew, B. K., & Sikorski, D. (2001). Can P/E ratio and bond yield be used to beat stock markets? *Multinational Finance Journal*, *5*(1), 59–86. https://doi.org/10.17578/5-1-3

Wong, W. K., Chow, S. C., Hon, T. Y., & Woo, K. Y. (2018). Empirical study on conservative and representative heuristics of Hong Kong small investors adopting momentum and contrarian trading strategies. *International Journal of Revenue Management*, *10*(2), 146–167. https://doi.org/10.1504/IJRM.2018.091643

Wong, W. K., Du, J., & Chong, T. T. L. (2005). Do the technical indicators reward chartists in Greater China stock exchanges? *Review of Applied Economics*, *1*(2), 183–205. https://www.rae.org.nz/archive.html

Wong, W. K., & Li, C. K. (1999). A note on convex stochastic dominance theory. *Economics Letters*, *62*(3), 293–300. https://doi.org/10.1016/S0165-1765(98)00235-2

Wong, W. K., Ma, C., Qiao, Z., Broll, U., & Vieito, J. P. T. (2026). New stochastic dominance theory for investors with risk-averse and risk-seeking utilities with applications including solutions for the Friedman-Savage paradox. *Review of Behavioral Finance*. Advance online publication. https://doi.org/10.1108/RBF-06-2024-0176

Wong, W. K., Manzur, M., & Chew, B. K. (2003). How rewarding is technical analysis? Evidence from Singapore stock market. *Applied Financial Economics*, *13*(7), 543–551. https://doi.org/10.1080/0960310022000020906

Wong, W. K., & McAleer, M. (2009). Mapping the presidential election cycle in US stock markets. *Mathematics and Computers in Simulation*, *79*(11), 3267–3277. https://doi.org/10.1016/j.matcom.2009.03.001

Wong, W. K., & Pham, M. T. (2022a). Could the test from the standard regression model make significant regression with autoregressive noise become insignificant? *The International Journal of Finance*, *34*(1), 1–18. https://doi.org/10.47260/ijf/341

Wong, W. K., & Pham, M. T. (2022b). Could the test from the standard regression model make significant regression with autoregressive noise become insignificant—A note. *The International Journal of Finance*, *34*(2), 19–39. https://doi.org/10.47260/ijf/342

Wong, W. K., & Pham, M. T. (2023a). Could the test from the standard regression model make significant regression with autoregressive Yt and Xt become insignificant? *The International Journal of Finance*, *35*(1), 1–19. https://doi.org/10.47260/ijf/351

Wong, W. K., & Pham, M. T. (2023b). Could the test from the standard regression model make significant regression with autoregressive Yt and Xt become insignificant—A note. *The International Journal of Finance*, *35*(2), 20–41. https://doi.org/10.47260/ijf/352

Wong, W. K., & Pham, M. T. (2025a). Could the correlation of a stationary series with a non-stationary series obtain meaningful outcomes? *Annals of Financial Economics*, *20*(3), Article 2550015. https://doi.org/10.1142/S2010495225500155

Wong, W. K., & Pham, M. T. (2025b). How to model a simple stationary series with a non-stationary series? *The International Journal of Finance*, *37*(1), 1–19. https://doi.org/10.47260/ijf/371

Wong, W. K., & Pham, M. T. (2026a). Could the panel regression be used to examine the relationship between I(0) and I(1) series? *Advances in Decision Sciences*, *30*(2). Advance online publication. https://doi.org/10.47654/ads.v30i2

Wong, W. K., & Pham, M. T. (2026b). Could we use correlation to examine panel data with I(0) and I(1) variables? *The International Journal of Finance*, *38*(1). Advance online publication. https://doi.org/10.47260/ijf/381

Wong, W. K., Pham, M. T., & Yue, M. (2024). Could regressing a stationary series on a non-stationary series obtain meaningful outcomes—a remedy. *The International Journal of Finance*, *36*, 1–20.

Wong, W. K., Phoon, K. F., & Lean, H. H. (2008). Stochastic dominance analysis of Asian hedge funds. *Pacific-Basin Finance Journal*, *16*(3), 204–223. https://doi.org/10.1016/j.pacfin.2007.10.001

Wong, W. K., Yeung, D., & Lu, R. (2023). The mean-variance rule for investors with reverse S-shaped utility. *Annals of Financial Economics*, *18*(1), Article 2250030. https://doi.org/10.1142/S2010495222500300

Wong, W. K., & Yue, M. (2024). Could regressing a stationary series on a non-stationary series obtain meaningful outcomes? *Annals of Financial Economics*, *19*(3), Article 2450011. https://doi.org/10.1142/S2010495224500118

Wong, W. K., Zhu, Z., Jiang, I. M., & Bouri, E. (2025). Arbitrage opportunities in no-arbitrage portfolios: The case of Bitcoin and Treasury Bills. *Investment Analysts Journal*, *55*(1), 55–86. https://doi.org/10.1080/10293523.2024.2446253