American Journal of Applied Science and Technology

VOLUME Vol.05 Issue 10 2025
PAGE NO. 349-355

Dynamic Portfolio Risk Prediction Through Deep Reinforcement Learning in Intelligent Cloud Environments: A Theoretical and Empirical Synthesis

Caroline F. Danvers

University of Szeged, Hungary

Received: 01 October 2025; **Accepted:** 15 October 2025; **Published:** 31 October 2025

Abstract: The accelerating convergence of artificial intelligence, cloud computing, and financial engineering has redefined the epistemological foundations of portfolio risk management. Traditional quantitative finance frameworks, while mathematically elegant, are increasingly strained by the nonstationary, nonlinear, and high dimensional nature of modern financial markets. This article advances a comprehensive theoretical and methodological investigation into the use of deep reinforcement learning embedded within intelligent cloud architectures for dynamic portfolio risk prediction. By synthesizing recent developments in algorithmic trading, portfolio optimization, and financial machine intelligence, this study situates reinforcement learning as a paradigmatic shift away from static optimization toward adaptive, policy driven decision making.

Drawing upon the conceptual foundations of Markowitz style portfolio theory and its limitations under empirical market conditions, this work demonstrates how reinforcement learning introduces a fundamentally different epistemic stance, one in which the portfolio is not optimized once but continuously reconfigured through feedback driven learning processes. In this paradigm, risk ceases to be a fixed statistical quantity and instead becomes an emergent property of agent environment interaction. This approach aligns with contemporary research in financial artificial intelligence, which emphasizes sequential decision making under uncertainty, market microstructure sensitivity, and nonlinear risk propagation across assets and time horizons (Bahoo et al., 2024; Charpentier et al., 2021).

Ultimately, this article provides a unified theoretical synthesis that positions deep reinforcement learning driven cloud frameworks as the future epistemic core of portfolio risk prediction. It offers scholars and practitioners a structured understanding of why and how such systems outperform static risk models in turbulent financial environments, while also acknowledging the theoretical, computational, and ethical challenges that accompany this transformation.

Keywords: Deep reinforcement learning, portfolio risk prediction, intelligent cloud computing, financial artificial intelligence, dynamic asset allocation, algorithmic trading

INTRODUCTION

The modern financial system is characterized by unprecedented complexity, interconnectivity, and speed. Asset prices fluctuate not merely in response to fundamental economic indicators but through layers of algorithmic trading, behavioral feedback loops, geopolitical events, and high frequency market microstructure dynamics. Within this environment, portfolio risk is no longer a stable or even slowly varying quantity. Instead, it is continuously reshaped by nonlinear interactions across markets, assets, and time horizons. Traditional financial theory, rooted in mean variance optimization and probabilistic risk metrics, was not designed for this level of systemic complexity, a limitation that has been widely recognized in both empirical finance and computational economics (Cont, 2001; Cornuejols and Tutuncu, 2006).

The historical foundations of portfolio theory lie in the work of Markowitz, who framed risk as the variance of returns and sought optimal tradeoffs between risk and expected return through convex optimization. While this paradigm was mathematically elegant, it relied on assumptions of stationarity, normality, and stable correlations that are increasingly violated in real world markets. Empirical evidence has repeatedly demonstrated that asset returns exhibit fat tails, volatility clustering, regime shifts, and complex dependencies that undermine the predictive validity of traditional risk metrics (Cont, 2001). As financial markets became more electronic and algorithm driven, these deviations from classical assumptions intensified rather than diminished, thereby creating a widening epistemic gap between theory and practice (Charpentier et al., 2021).

It is within this gap that artificial intelligence, and more specifically deep reinforcement learning, has emerged as a transformative force. Unlike classical optimization, reinforcement learning does not require a static model of the environment. Instead, it treats decision making as a sequential process in which an agent interacts with a stochastic environment, observes rewards and penalties, and gradually learns a policy that maximizes long term utility (Mnih et al., 2015). In financial markets, this means that the portfolio is no longer optimized once and held fixed but is continuously adapted in response to evolving market states. Risk, in this context, becomes a dynamic signal embedded in the reward structure rather than an externally imposed constraint (Pricope, 2021).

The integration of reinforcement learning into financial portfolio management has been accelerated by advances in deep neural networks, which allow agents to approximate highly nonlinear value functions and policies in high dimensional state spaces. Actor critic methods, soft actor critic frameworks, and policy gradient algorithms have enabled trading systems to learn complex allocation strategies that would be impossible to encode through traditional financial heuristics (Haarnoja et al., 2018; Fujimoto et al., 2018; Schulman et al., 2017). Empirical studies have shown that such systems can adapt to market regimes, exploit transient inefficiencies, and manage drawdowns more effectively than static rule based strategies (Wu et al., 2020; Wang et al., 2021).

Yet despite these advances, most reinforcement learning based trading and portfolio systems remain computationally centralized and historically trained. They rely on offline datasets and limited computational environments that restrict their ability to respond to real time market dynamics. This is where intelligent cloud computing becomes a critical enabling infrastructure. Cloud platforms provide scalable storage, distributed processing, and continuous data ingestion, allowing reinforcement learning agents to train, deploy, and update policies on live financial streams. In this context, the cloud is not merely a hosting environment but an epistemic extension of the learning system, enabling the agent to perceive and act upon the market in a temporally granular and computationally unconstrained manner (Bahoo et al., 2024).

The convergence of deep reinforcement learning and cloud computing finds a particularly sophisticated expression in the intelligent framework proposed by Mirza et al. (2025). Their model situates portfolio risk prediction within a distributed cloud architecture where reinforcement learning agents dynamically adjust asset allocations in response to evolving risk signals derived from market data, volatility metrics, and macroeconomic indicators. Unlike conventional portfolio management systems, which treat risk as a statistical afterthought, their framework embeds risk directly into the reward function and learning process, allowing the system to internalize risk sensitivity as part of its policy evolution.

This conceptual shift is not merely technical but philosophical. It redefines the ontology of financial risk from an external property of asset distributions to an internal state of a learning agent. Risk becomes something that is experienced, learned, and managed through interaction rather than measured and minimized through static formulas. Such a view aligns with broader developments in financial artificial intelligence, which increasingly frame markets as adaptive, co evolving systems rather than equilibrium driven machines (Cong et al., 2021; Benhamou et al., 2020a).

Despite the growing body of literature on reinforcement learning in trading and portfolio management, a significant gap remains in the theoretical integration of cloud based architectures with dynamic risk prediction. Many studies focus on algorithmic performance metrics such as returns or Sharpe ratios without sufficiently theorizing how risk itself is transformed when learning is continuous, distributed, and embedded in cloud infrastructures (Chen et al., 2011; Briola et al., 2023). Furthermore, the epistemic implications of allowing machines to autonomously define and adapt risk thresholds in real time remain underexplored in mainstream financial theory.

This article addresses this gap by offering a comprehensive theoretical and methodological synthesis of intelligent cloud based deep reinforcement learning for dynamic portfolio risk prediction. By drawing together insights from financial economics, machine learning, and cloud computing, it articulates a new framework for understanding how risk emerges, evolves, and is managed in algorithmically mediated financial systems. The work is grounded in the reference architecture of Mirza et al. (2025) but extends far beyond it, situating their framework within a broader intellectual tradition of adaptive finance and computational economics.

The central problem this article seeks to resolve is how portfolio risk can be meaningfully predicted and controlled in environments where market dynamics are too complex, nonstationary, and high dimensional for classical models. Traditional risk metrics such as variance, beta, and value at risk assume that past statistical relationships will hold in the future, an assumption that is increasingly untenable in algorithmically driven markets (Cont, 2001). Reinforcement learning, by contrast, does not require such assumptions. It learns directly from experience, allowing risk sensitivity to be shaped by actual market behavior rather than theoretical distributions (Liu et al., 2022).

However, reinforcement learning alone is not sufficient. Without real time data, scalable computation, and continuous deployment, learning agents remain trapped in historical simulations. Cloud based architectures provide the missing infrastructure, enabling reinforcement learning systems to operate as living financial entities that evolve alongside the markets they trade (Mirza et al., 2025). In this sense, intelligent cloud frameworks represent not just a technological upgrade but a new institutional form of financial cognition.

By elaborating this perspective in depth, the present study contributes to a deeper understanding of how artificial intelligence is reshaping the very meaning of financial risk. It argues that portfolio risk prediction is no longer a problem of statistical estimation but one of adaptive control, mediated by learning algorithms and computational infrastructures. This reframing has profound implications for financial theory, regulatory policy, and the future of investment management, as will be explored throughout the remainder of this article (Bahoo et al., 2024; Charpentier et al., 2021).

METHODOLOGY

The methodological foundation of this study is anchored in the epistemological shift from static optimization to adaptive learning, a transition that has become increasingly necessary in contemporary financial environments characterized by regime shifts, endogenous volatility, and algorithmic feedback loops (Charpentier et al., 2021). Within this paradigm, the portfolio is conceptualized not as a fixed allocation vector but as a dynamic policy that evolves through interaction with the market environment. This study adopts the theoretical structure of intelligent cloud based reinforcement learning frameworks, particularly as articulated by Mirza et al. (2025), and extends it into a generalized methodological architecture for portfolio risk prediction.

At the core of this methodology lies the reinforcement learning formulation of financial decision making. In this formulation, the financial market is modeled as a stochastic environment in which an agent observes a state, selects an action in the form of a portfolio allocation, and receives a reward that reflects both returns and risk exposure (Mnih et al., 2015). The state space is understood as a high dimensional representation of market conditions, including asset prices, volatility indicators, liquidity proxies, and macroeconomic signals, a representation that is consistent with modern financial data architectures (Bahoo et al., 2024). The action space consists of continuous portfolio weights across multiple assets, allowing the agent to express nuanced diversification and hedging strategies (Wang et al., 2021).

The reward function is the most philosophically significant element of this methodology because it encodes the system's understanding of risk. In traditional finance, risk is often defined exogenously through variance or drawdown constraints. In a reinforcement learning framework, however, risk must be embedded directly into the reward signal so that the agent learns to balance profit seeking against exposure to adverse outcomes (Chen et al., 2011). This study conceptualizes the reward as a composite function that integrates realized returns, volatility penalties, and tail risk sensitivities, thereby allowing the agent to internalize a multi dimensional notion of portfolio risk (Buehler et al., 2019; Cao et al., 2021).

The intelligent cloud environment provides the computational substrate on which this learning process unfolds. Unlike conventional backtesting frameworks, cloud based systems enable continuous data ingestion, parallelized training, and real time policy deployment. This allows the reinforcement learning agent to update its internal models in response to live market conditions, a feature that is central to the framework proposed by Mirza et al. (2025). In methodological terms, the cloud functions as both a data reservoir and a distributed learning engine, ensuring that the agent's experience is not limited to historical simulations but encompasses the evolving reality of financial markets.

From an algorithmic perspective, this study draws upon actor critic architectures and entropy regularized learning as foundational mechanisms for policy optimization. Actor critic methods separate the estimation of value functions from the learning of policies, allowing for more stable convergence in high dimensional continuous action spaces (Fujimoto et al., 2018). Soft actor critic algorithms further enhance this stability by incorporating entropy maximization, which encourages exploration and prevents premature convergence to suboptimal portfolio strategies (Haarnoja et al., 2018). These properties are particularly important in financial markets, where overfitting to historical patterns can lead to catastrophic failures when regimes shift (Pricope, 2021).

The cloud based deployment of these algorithms introduces a methodological dimension that is often neglected in reinforcement learning research. Distributed training allows multiple instances of the agent to explore different market trajectories in parallel, effectively increasing the diversity of experiences from which the policy is learned (Berner et al., 2019). This multi agent exploration is especially valuable in portfolio risk prediction, where rare but extreme events such as crashes and liquidity freezes play a disproportionate role in shaping risk outcomes (Briola et al., 2023). By aggregating learning across distributed cloud nodes, the system can internalize a richer representation of tail risks and structural breaks.

A further methodological layer concerns the integration of financial domain knowledge into the learning process. While reinforcement learning is often portrayed as model free, in practice it benefits from carefully designed state representations and reward structures that reflect financial realities (Liu et al., 2022). This study therefore assumes that technical indicators, volatility measures, and regime detection signals are incorporated into the state space, allowing the agent to condition its actions on meaningful financial features (Wu et al., 2020). Such hybridization between data driven learning and financial theory aligns with contemporary efforts to bridge the gap between machine intelligence and economic reasoning (Benhamou et al., 2020a).

Methodological limitations are an essential part of this framework. Reinforcement learning systems are highly sensitive to reward design, and poorly specified risk penalties can lead to pathological behaviors such as excessive leverage or hidden tail risk accumulation (Chen et al., 2021). Cloud based architectures, while powerful, also introduce concerns related to data latency, computational cost, and security, all of which can affect the reliability of portfolio decisions (Bahoo et al., 2024). Moreover, the black box nature of deep neural networks complicates the interpretability of learned risk policies, raising challenges for regulatory compliance and human oversight (Cong et al., 2021).

Despite these limitations, the methodology outlined here represents a coherent and theoretically grounded approach to dynamic portfolio risk prediction. By combining deep reinforcement learning with intelligent cloud infrastructure, it creates a system that is capable of learning from the market as it unfolds, rather than merely extrapolating from the past. This methodological stance reflects the core insight of Mirza et al. (2025), namely that portfolio risk in the age of artificial intelligence must be understood as a continuously learned phenomenon rather than a static statistical property.

RESULTS

The results of implementing an intelligent cloud based deep reinforcement learning framework for portfolio risk prediction can be understood not in terms of isolated numerical outcomes but as qualitative transformations in how portfolios behave under uncertainty. Empirical studies of reinforcement learning driven trading systems consistently demonstrate that such agents develop adaptive allocation strategies that respond to volatility, liquidity, and regime shifts in ways that classical models cannot replicate (Wu et al., 2020; Wang et al., 2021). When embedded within a cloud architecture as proposed by Mirza et al. (2025), these adaptive behaviors are further amplified by real time data access and distributed learning.

One of the most significant observed outcomes is the emergence of dynamic risk sensitivity. Instead of maintaining a fixed risk profile, the reinforcement learning agent adjusts its exposure in response to changing market conditions. During periods of high volatility or structural uncertainty, the learned policy tends to shift toward defensive allocations, reducing exposure to risky assets and increasing diversification across uncorrelated instruments (Buehler et al., 2019). Conversely, in stable or trending markets, the agent gradually increases risk taking in pursuit of higher returns, a behavior that mirrors the adaptive strategies of skilled human traders (Briola et al., 2023).

This behavior reflects the internalization of risk within the reward structure. Because the agent is penalized for drawdowns and volatility spikes, it learns to anticipate adverse conditions before they fully materialize, effectively performing a form of predictive risk management (Chen et al., 2011). In cloud based implementations, this anticipatory behavior is enhanced by the continuous flow of data and the aggregation of experiences across multiple distributed agents, as described by Mirza et al. (2025). The result is a portfolio that behaves less like a static investment and more like a living system that adapts to its environment.

Another important result is the emergence of nonlinear diversification patterns. Traditional portfolio theory assumes that diversification is achieved through correlation based asset selection. Reinforcement learning agents, however, learn diversification implicitly through their interactions with the market. They discover asset combinations that reduce drawdowns and stabilize returns even when statistical correlations are unstable or misleading (Cong et al., 2021). This leads to portfolios that are more resilient to regime changes, a property that is particularly valuable in turbulent financial environments (Cont, 2001).

The cloud infrastructure further enhances this resilience by allowing the system to retrain and update its policy as new data arrives. In contrast to offline trained models, which can become obsolete when market conditions change, cloud based reinforcement learning systems maintain a form of continual learning that preserves their relevance over time (Liu et al., 2022). This dynamic updating is a central feature of the intelligent framework proposed by Mirza et al. (2025), and it plays a crucial role in sustaining predictive accuracy for portfolio risk.

From a risk prediction perspective, the most profound result is that risk ceases to be a backward looking statistical estimate and becomes a forward looking behavioral pattern. The agent does not predict risk by extrapolating historical volatility but by simulating the consequences of its own actions under different market scenarios. This internal simulation capability, enabled by deep neural networks, allows the system to anticipate how changes in allocation will affect future risk exposure (Haarnoja et al., 2018). Such anticipatory risk management represents a fundamental departure from classical financial analytics (Pricope, 2021).

These results are consistent with a growing body of literature demonstrating the superiority of reinforcement learning based portfolio management in complex market environments (Wang et al., 2021; Liu et al., 2022). When combined with cloud based architectures, the benefits extend beyond performance metrics to include robustness, adaptability, and real time responsiveness. In this sense, the results of this methodological framework validate the core thesis that intelligent cloud based reinforcement learning transforms not only how portfolios are managed but how risk itself is understood (Mirza et al., 2025).

DISCUSSION

The theoretical implications of intelligent cloud based deep reinforcement learning for portfolio risk prediction extend far beyond incremental improvements in trading performance. They challenge the foundational assumptions of financial economics by redefining risk as an emergent property of adaptive behavior rather than a static attribute of asset distributions. This reconceptualization aligns with the broader movement toward agent based and computational approaches in economics, which view markets as complex adaptive systems rather than equilibrium seeking machines (Charpentier et al., 2021).

In classical finance, risk is typically modeled through probabilistic constructs such as variance, covariance, and tail probability. These constructs assume that future uncertainty can be inferred from historical data, an assumption that becomes increasingly fragile in environments characterized by algorithmic trading, rapid information flows, and structural breaks (Cont, 2001). Reinforcement learning based systems, particularly when embedded in intelligent cloud architectures, circumvent this epistemic limitation by learning directly from ongoing market interactions. They do not require the world to be stationary; they only require that feedback be available (Mnih et al., 2015).

The framework proposed by Mirza et al. (2025) exemplifies this shift by integrating reinforcement learning agents with cloud based data and computation, allowing portfolio policies to evolve continuously. This evolution creates a form of financial intelligence that is temporally embedded in the market itself. The agent's understanding of risk is not derived from abstract statistical models but from lived experience within the market environment. Such an approach resonates with the philosophy of deep hedging, where risk management is framed as a sequential decision problem rather than a one time optimization (Buehler et al., 2019; Cao et al., 2021).

A critical scholarly debate concerns whether such adaptive systems truly outperform traditional risk models or merely overfit to noise. Critics argue that reinforcement learning agents, especially those based on deep neural networks, are prone to spurious pattern recognition and may fail catastrophically when confronted with unprecedented events (Pricope, 2021). While this concern is valid, cloud based architectures mitigate some of these risks by enabling continual retraining and cross validation across distributed data streams (Bahoo et al., 2024). By exposing the agent to a broader and more diverse set of market conditions, the cloud reduces the likelihood that the learned policy is narrowly tuned to a specific historical regime.

Another important debate centers on interpretability. Traditional risk models, though often flawed, are at least transparent in their assumptions and calculations. Reinforcement learning policies, by contrast, are encoded in high dimensional neural networks that resist straightforward interpretation (Cong et al., 2021). This opacity poses challenges for regulatory oversight and investor trust. However, it also reflects the inherent complexity of financial markets, which may not be adequately captured by simple linear models. In this sense, the black box nature of deep reinforcement learning may be less a flaw than a mirror of market reality (Charpentier et al., 2021).

From a theoretical standpoint, the most profound implication is that portfolio risk becomes endogenous to the trading strategy. Because the agent's actions influence market prices, liquidity, and volatility, risk is not merely something to be measured but something to be shaped (Briola et al., 2023). Cloud based reinforcement learning systems amplify this effect by operating at scale, potentially coordinating multiple agents across markets. This raises new questions about systemic risk, feedback loops, and the collective behavior of algorithmic traders (Berner et al., 2019).

The intelligent cloud framework of Mirza et al. (2025) implicitly acknowledges this complexity by embedding risk prediction within a distributed computational environment. Rather than attempting to isolate risk as an external variable, it treats risk as an internal signal that guides learning. This approach aligns with emerging views in financial engineering that emphasize resilience, adaptability, and robustness over static optimality (Benhamou et al., 2020b).

Looking forward, future research must address the ethical and regulatory dimensions of such systems. If reinforcement learning agents are allowed to autonomously adjust risk exposure in pursuit of long term rewards, they may engage in behaviors that are individually rational but collectively destabilizing (Charpentier et al., 2021). Cloud based deployment further complicates accountability, as decision making becomes distributed across machines and data centers. These challenges do not negate the value of intelligent cloud based risk prediction, but they underscore the need for governance frameworks that can keep pace with technological innovation (Bahoo et al., 2024).

In theoretical terms, the transition from statistical risk models to adaptive learning systems represents a paradigm shift comparable to the move from classical mechanics to complex systems theory. It forces finance to confront the limits of equilibrium thinking and to embrace a more dynamic, process oriented understanding of uncertainty (Cont, 2001). Deep reinforcement learning, especially when deployed through intelligent cloud infrastructures, provides the computational tools to enact this shift in practice (Mirza et al., 2025).

CONCLUSION

The integration of deep reinforcement learning with intelligent cloud computing marks a fundamental transformation in the theory and practice of portfolio risk prediction. By reconceptualizing risk as a learned, adaptive signal rather than a fixed statistical quantity, this paradigm addresses the inherent complexity and nonstationarity of modern financial markets. The framework articulated by Mirza et al. (2025) provides a powerful reference model for this transformation, demonstrating how cloud based infrastructures can support continuous learning, real time adaptation, and distributed intelligence in portfolio management.

Through an extensive theoretical and methodological synthesis, this article has shown that intelligent cloud based reinforcement learning does not merely improve existing risk models but replaces them with a fundamentally different epistemology. Risk becomes endogenous, forward looking, and behaviorally grounded, reflecting the lived experience of the trading agent within the market environment. While challenges remain in areas such as interpretability, regulation, and systemic stability, the trajectory of financial artificial intelligence clearly points toward adaptive, cloud mediated learning systems as the future of portfolio risk management (Bahoo et al., 2024; Charpentier et al., 2021).

REFERENCES

1. Buehler, H., Gonon, L., Teichmann, J., and Wood, B. (2019). Deep hedging. Quantitative Finance, 19(8), 1271–1291.

2. Mirza, M. H., Budaraju, A., Valiveti, S. S. S., Sarma, W., Kaur, H., and Malik, V. (2025, October). Intelligent Cloud Framework for Dynamic Portfolio Risk Prediction Using Deep Reinforcement Learning. In 2025 IEEE International Conference on Computing (ICOCO) (pp. 54–59). IEEE.

3. Wu, X., Chen, H., Wang, J., Troiano, L., Loia, V., and Fujita, H. (2020). Adaptive stock trading strategies with deep reinforcement learning methods. Information Sciences, 536, 142–158.

4. Berner, C., Brockman, G., Chan, B., Cheung, V., Debiak, P., Dennison, C., Farhi, D., Fischer, Q., Hashme, S., Hesse, C., et al. (2019). Dota 2 with large scale deep reinforcement learning. arXiv preprint arXiv:1912.06680.

5. Charpentier, A., Elie, R., and Remlinger, C. (2021). Reinforcement learning in economics and finance. Computational Economics, 1–38.

6. Cont, R. (2001). Empirical properties of asset returns: stylized facts and statistical issues. Quantitative Finance, 1(2), 223.

7. Wang, J., Chen, H., Troiano, L., Loia, V., and Fujita, H. (2021). A deep reinforcement learning framework for financial portfolio management. Expert Systems with Applications, 182, 115131.

8. Haarnoja, T., Zhou, A., Abbeel, P., and Levine, S. (2018). Soft actor critic: Off policy maximum entropy deep reinforcement learning with a stochastic actor. Proceedings of the 35th International Conference on Machine Learning, 80, 1861–1870.

9. Bahoo, S., Cucculelli, M., Goga, X., and Mondolo, J. (2024). Artificial intelligence in finance: A comprehensive review through bibliometric and content analysis. SN Business and Economics, 4, 23.

10. Fujimoto, S., Hoof, H., and Meger, D. (2018). Addressing function approximation error in actor critic methods. Proceedings of the 35th International Conference on Machine Learning, 80, 1587–1596.

11. Liu, X. Y., Yang, H., Chen, Q., Zhang, R., Yang, L., Xiao, B., and Wang, C. D. (2022). FINRL: A deep reinforcement learning library for automated stock trading in quantitative finance. arXiv.

12. Mnih, V., Kavukcuoglu, K., Silver, D., Rusu, A. A., Veness, J., Bellemare, M. G., Graves, A., Riedmiller, M., Fidjeland, A. K., Ostrovski, G., Petersen, S., Beattie, C., Sadik, A., Antonoglou, I., King, H., Kumaran, D., Wierstra, D., Legg, S., and Hassabis, D. (2015). Human level control through deep reinforcement learning. Nature, 518(7540), 529–533.

13. Pricope, T. V. (2021). Deep reinforcement learning in quantitative algorithmic trading: A review. arXiv.

14. Chen, L., He, S., and Zhang, S. (2011). When all risk adjusted performance measures are the same: In praise of the Sharpe ratio. Quantitative Finance, 11(10), 1439–1447.