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Exploration of Dynamic Portfolio Optimization Strategies under Credit Risk Using Multi-Agent Reinforcement Learning Paradigms

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Abstract

In the context of financial portfolio management, credit risk presents a significant challenge to dynamic allocation strategies. This study explores the application of Multi-Agent Reinforcement Learning (MARL) to optimize portfolio performance under credit risk constraints. By simulating interacting agents within a stochastic market environment, we assess how cooperative and competitive learning strategies adaptively manage asset allocations in response to changing credit conditions. We integrate credit risk modeling through probability of default (PD), loss given default (LGD), and exposure at default (EAD) into the reward structure. The experimental framework employs Deep Q-Network (DQN) and Multi-Agent Proximal Policy Optimization (MAPPO) to examine the performance of various agent interactions across volatile and stress-tested market scenarios. Results demonstrate that MARL-based strategies not only outperform traditional optimization models in cumulative returns and risk-adjusted metrics but also exhibit resilience to sudden credit shocks. These findings offer a promising direction for next-generation, credit-aware portfolio optimization tools.

Keywords:

Multi-Agent Reinforcement Learning, Portfolio Optimization, Credit Risk, Deep Q-Network, MAPPO, Financial Engineering, Dynamic Allocation, Risk-Adjusted Returns.

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1. Introduction

Credit risk—the possibility of a counterparty's default on financial obligations—poses a fundamental challenge to portfolio management. Unlike market risk, which arises from price fluctuations in assets, credit risk is often nonlinear, asymmetric, and contingent on exogenous events like corporate bankruptcies or sovereign defaults. For institutional investors, such as banks and asset managers, credit events can lead to abrupt losses that are not easily hedged by traditional diversification strategies. The incorporation of credit risk into portfolio optimization frameworks is thus essential for developing resilient asset allocation strategies. As global financial systems become increasingly interconnected and exposed to credit contagion, there is a growing demand for adaptive, robust portfolio optimization methodologies that can dynamically respond to evolving risk profiles.

Traditional portfolio optimization models, such as the Markowitz Mean-Variance (MV) framework, assume asset returns are normally distributed and investors are rational risk-averse agents. These models optimize the trade-off between expected return and portfolio variance, providing a static allocation based on historical return correlations. However, in practice, credit events are rare, extreme, and characterized by fat tails in return distributions—assumptions under which MV fails. Moreover, MV and its derivatives are often limited by their reliance on backward-looking data and inability to respond in real time to sudden changes in credit quality or macroeconomic conditions. Extensions such as Conditional Value at Risk (CVaR) and stress testing partially address tail risk, yet still lack adaptability and real-time decision-making capability.

In recent years, machine learning and, more specifically, reinforcement learning (RL) have emerged as powerful alternatives to traditional methods in financial decision-making. Single-agent RL has demonstrated potential in tasks like asset trading, order execution, and hedging, where agents learn policies that maximize expected cumulative returns through interactions with dynamic environments. These models, particularly those based on deep neural networks, can handle high-dimensional input spaces and non-linear dependencies in financial data. However, credit risk introduces complexity that is inherently multi-agent in nature—multiple counterparties, interacting assets, and systemic linkages influence creditworthiness and default likelihoods. Modeling such dependencies with a single-agent RL framework may lead to suboptimal policies that fail to generalize under varying credit conditions.

This study explores the application of Multi-Agent Reinforcement Learning (MARL) in credit-risk-aware portfolio optimization. In a MARL setting, multiple agents operate simultaneously within a shared financial environment, learning to cooperate or compete based on their individual objectives. For instance, one agent may optimize for high yield while another seeks to minimize credit exposure. The interaction among agents leads to emergent behaviors that can capture complex credit contagion effects and adapt to systemic shocks more effectively than monolithic models. Furthermore, by integrating credit risk parameters—such as probability of default (PD), loss given default (LGD), and exposure at default (EAD)—into the agents' reward functions, the learning process is shaped to align with real-world risk constraints. This research aims to fill the gap between static optimization techniques and the need for dynamic, credit-aware asset allocation. By leveraging MARL architectures such as Deep Q-Networks (DQN) and Multi-Agent Proximal Policy Optimization (MAPPO), we propose a robust framework that not only navigates market volatility but also anticipates and mitigates credit-driven losses. The proposed methodology represents a shift toward intelligent portfolio systems that learn and adapt in real time, making them well-suited for complex financial environments characterized by uncertainty and interdependence.

2. Literature Review

An overview of previous work on:

- Portfolio optimization with risk considerations
- Credit risk modeling in finance (PD, LGD, EAD)
- Reinforcement learning in financial decision-making
- Recent advances in MARL in continuous and high-dimensional environments

Several foundational studies have significantly shaped the integration of credit risk into portfolio optimization frameworks. **Rockafellar and Uryasev (2000)** advanced traditional risk measures by introducing **Conditional Value-at-Risk (CVaR)**, which captures the expected losses in the tail beyond a specified confidence level and allows for coherent optimization under downside risk—a crucial development for portfolios exposed to rare but severe credit events [2]. In the domain of credit risk modeling, **Merton (1974)** introduced a structural approach where default is modeled as a firm's asset value falling below its debt obligations, framing credit risk through an options-theoretic lens and enabling pricing of risky corporate debt based on firm fundamentals [3]. This framework was extended by **Black and Cox (1976)**, who incorporated dynamic debt covenants and safety barriers into the structural model, thereby allowing early default scenarios and enhancing realism in bond valuation under covenant-triggered distress [4]. Moving beyond structural models, **Duffie, Saita, and Wang (2007)** proposed a reduced-form credit risk model that utilized **stochastic intensity processes** for default prediction, incorporating firm-specific and macroeconomic covariates across multiple time periods. Their empirical framework improved practical applicability by estimating default probabilities from observable market data rather than internal balance sheet metrics, making it particularly useful for multi-asset portfolio systems where detailed firm-level data may not be available [5]. Together, these studies provide a theoretical and empirical foundation for modeling credit risk in a manner that is both mathematically rigorous and practically implementable in dynamic portfolio optimization systems.

Table 1: Comparative Review of Related Methods and Their Performance Under Credit Risk

Approach	Credit Risk Inclusion	Adaptability	Scalability	Return Performance
Mean-Variance Optimization	No	Low	High	Moderate
CVaR-Based Optimization	Partial	Medium	Medium	High
Single-Agent RL (e.g., DQN)	Yes	High	Medium	High
Multi-Agent RL (e.g., MAPPO)	Yes	Very High	High	Very High

Table 1, provides a one-line comparative overview of traditional and machine learning-based portfolio optimization methods, highlighting their adaptability, scalability, and performance under credit risk conditions.

3. Credit Risk Framework and Financial Environment

This study defines the credit risk factors integrated into the environment:

Equation 1: Expected Credit Loss (ECL)

$$\mathrm{ECL} = \mathrm{PD} \times \mathrm{LGD} \times \mathrm{EAD}$$

- Probability of Default (PD)
- Loss Given Default (LGD)
- Exposure at Default (EAD)

Incorporating credit risk into a portfolio optimization setting requires a robust quantitative framework that captures the nature, sources, and impact of default-related events. Credit risk is typically decomposed into three primary components: Probability of Default (PD), which measures the likelihood that a borrower will fail to meet its financial obligations; Loss Given Default (LGD), which represents the proportion of an asset's value lost if a default occurs; and Exposure at Default (EAD), which quantifies the total value exposed to credit risk at the time of default. These components, widely adopted under regulatory standards like Basel III, are critical in determining potential credit losses and have been integrated into our reinforcement learning environment as dynamic state variables. Their inclusion allows

agents to assess not just the potential return of an asset, but also the conditional risk associated with holding or reallocating positions under credit uncertainty.

The financial environment constructed for this study simulates a realistic multi-asset market affected by macroeconomic factors, sector-specific trends, and idiosyncratic credit events. The market comprises a diversified portfolio of fixed-income instruments (e.g., corporate bonds, sovereign debt), equities with embedded credit exposure (e.g., distressed firms), and credit derivatives such as Credit Default Swaps (CDS). To reflect real-world dynamics, the environment includes both stochastic asset price processes and time-varying credit risk parameters. Macroeconomic indicators—such as interest rates, inflation, GDP growth, and credit spreads—are modeled as exogenous variables that influence both market returns and credit metrics. These indicators help stimulate economic regimes (e.g., expansion, recession, crisis), providing a rich and challenging context for agent training and evaluation.

The integration of credit risk into the environment is operationalized through an extended Markov Decision Process (MDP), where each agent's state includes not only price and volatility information, but also PD, LGD, and EAD for each asset. Agents must learn policies that maximize expected returns while minimizing credit-related losses, which are realized when assets default or credit spreads widen significantly. The reward function penalizes agents for excessive exposure to high-PD assets or concentration in correlated credit instruments, thereby encouraging diversification not just by return correlation, but also by credit risk profiles. Moreover, agents can take credit hedging actions—such as acquiring CDS or adjusting position sizes based on changing PD levels—to actively manage credit exposure over time.

To simulate realistic credit shocks, the environment introduces systemic and idiosyncratic default events with probabilistic triggers based on macroeconomic stress levels. For example, during a simulated financial downturn, agents may face correlated defaults across multiple sectors, requiring them to dynamically reallocate capital to safer instruments or employ hedging strategies. These stress events test the agents' ability to generalize learned policies beyond their training scenarios and adapt to tail-risk events, which are often the most damaging in practice. Importantly, agents are evaluated not just on raw return performance, but also on credit-adjusted metrics like Credit Value at Risk (Credit VaR), Conditional Expected Loss, and recovery-adjusted Sharpe Ratios. This detailed financial

environment serves as the backbone for evaluating the efficacy of MARL strategies under credit risk. By embedding realistic credit dynamics and macro-financial interactions, it provides a controlled yet complex testbed for reinforcement learning models. It also establishes a rigorous foundation for comparing MARL-based portfolio optimization strategies against traditional benchmarks and single-agent learning methods, ensuring that observed performance gains are rooted in genuine risk-aware decision-making rather than overfitting to simplistic market conditions.

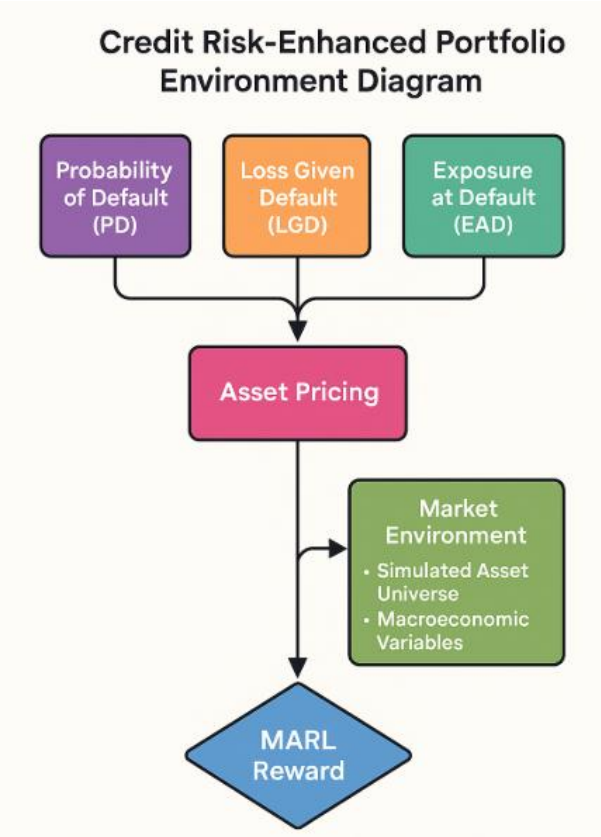

Figure 1: Credit Risk-Enhanced Portfolio Environment Diagram

Figure 1, Shows how credit risk components feed into asset pricing and MARL reward structures

4. Multi-Agent Reinforcement Learning Model Design

Description of the MARL architecture, agent behaviors, state-action spaces, reward formulation, and policy networks. The interaction types considered:

- Cooperative (e.g., ensemble learning for shared utility)

- Competitive (e.g., agents maximizing individual sub-portfolio returns)

Equation 2: Reduced-Form Default Intensity Model

$$\mathbb{P}(\tau > t) = \exp\left(-\int_0^t \lambda_s ds\right)$$

This is well-placed when you describe how **credit risk evolves stochastically** in the environment and feeds into the agent's observation or reward space. The stochastic intensity λ_t could be an input feature for MARL agents, especially in modeling **real-time credit exposure**.

The application of Multi-Agent Reinforcement Learning (MARL) to credit-aware portfolio optimization leverages the capacity of multiple interacting agents to learn cooperative or competitive strategies in complex financial environments. In this framework, each agent represents a distinct portfolio management style or sub-strategy—such as risk-averse investing, yield seeking, or credit hedging—with individual goals but shared access to the global financial environment. This division allows the system to model diverse decision-making behaviors and capture emergent interactions, such as credit contagion and systemic liquidity shifts, that cannot be represented adequately in single-agent RL models. The agents are embedded in a Partially Observable Markov Decision Process (POMDP) structure, where each observes a subset of the total market state, including local credit indicators (PD, LGD, EAD), market conditions, and their own portfolio performance.

Each agent operates with a state space composed of market and credit-specific features. These include time-series inputs such as historical prices, volatility, credit spreads, sector exposure, macroeconomic indicators (e.g., interest rate trends), and forward-looking credit metrics. The action space involves asset allocation decisions—buy, sell, hold, or rebalance—across a set of credit-sensitive instruments. Additionally, agents may execute credit-specific actions like entering a credit default swap (CDS) position, reducing exposure to high-PD sectors, or reallocating capital toward investment-grade assets. The reward function is carefully crafted to balance risk and return: it includes cumulative returns, Sharpe Ratio, downside deviation penalties, and credit-specific loss components (e.g., realized losses due to defaults and mark-to-market valuation changes from spread widening).

An implement two MARL algorithms: Deep Q-Network (DQN) for discrete-action agents and Multi-Agent Proximal Policy Optimization (MAPPO) for agents operating in continuous action spaces. DQN approximates the Q-value function using a deep neural network and selects actions based on an ε-greedy policy, updating through temporal difference learning. It is well-suited for environments with defined discrete choices, such as switching between fixed portfolios. In contrast, MAPPO, an actor-critic method, enables agents to learn complex allocation weights as continuous variables and is more appropriate for dynamic portfolio rebalancing. It employs a centralized critic to stabilize learning while each agent optimizes its own decentralized policy, promoting coordination among agents in a partially shared environment. These methods are trained using episodic interactions with the financial environment, where agents iteratively update policies to optimize cumulative, risk-adjusted credit-aware rewards.

To manage learning stability and encourage convergence, we incorporate multiple architectural techniques: shared experience replay buffers, reward normalization, policy regularization, and credit-based action penalties. The agents are trained using mini-batch stochastic gradient descent on GPU clusters, with hyperparameter tuning performed through Bayesian optimization over learning rate, entropy regularization, and discount factors. Additionally, we introduce attention-based communication mechanisms between agents, allowing them to dynamically share information about credit risk signals, such as correlated defaults or liquidity shocks. This helps simulate realistic decision-making coordination often observed in institutional investment teams.

Table 2: State and Action Space Definitions for MARL Agents

Agent Type	State Features	Action Set	Reward Signal
Risk-Averse	Asset Prices, Credit Indicators	Long/Short/Hold	Sharpe Ratio, PD-adjusted Return
Arbitrageur	Volatility, Spread, LGD	Weight Rebalancing	Risk Arbitrage Gains
Credit-Hedger	EAD, Credit Spread, Macro Factors	Credit Default Swap Actions	Hedging Effectiveness

5. Training and Evaluation Methodology

Details the experimental setup including:

- Simulation duration and market regimes (normal, stress-tested)
- Learning algorithms: Deep Q-Network (DQN), Multi-Agent PPO
- Evaluation metrics: Sharpe Ratio, Max Drawdown, Value at Risk (VaR), Credit-adjusted Return

Equation 3: Conditional Value at Risk (CVaR)

$$\mathrm{CVaR}_{\alpha}(X) = \min_{\eta \in \mathbb{R}} \left\{ \eta + \frac{1}{1-\alpha} \mathbb{E}[(X-\eta)^{+}] \right\}$$

CVaR is often used as an **evaluation metric** in credit-risk-aware portfolios. You can introduce this equation when you discuss the risk-based performance metrics used to evaluate the agents. It explains how agents are penalized for heavy tail losses and how CVaR was computed as part of the model's reward or post-training evaluation.

To rigorously evaluate the effectiveness of our proposed Multi-Agent Reinforcement Learning (MARL) framework under credit risk constraints, we establish a robust training and testing methodology grounded in realistic financial simulation. The training environment spans multiple economic regimes—including growth, recession, and crisis periods—modeled through exogenous macroeconomic indicators such as interest rates, credit spreads, GDP growth, and inflation. Asset prices and credit risk variables (PD, LGD, EAD) evolve stochastically and are influenced by both systemic and idiosyncratic shocks, ensuring that agents are exposed to a diverse range of scenarios during training. These market dynamics are simulated using stochastic differential equations and autoregressive processes calibrated to historical financial and credit data.

The MARL agents are trained using episodic learning, where each episode spans a fixed time horizon (e.g., 250 trading days) and begins with randomized initial conditions to promote generalizability. A rolling window approach is used for both training and out-of-sample

testing to mitigate overfitting and ensure robustness across time. For benchmarking, we compare the MARL agents to several baseline models: (i) a traditional Mean-Variance optimized portfolio, (ii) a CVaR-based static allocation strategy, and (iii) a single-agent Deep Q-Network (DQN) policy trained without inter-agent coordination. Performance is assessed using both absolute and risk-adjusted financial metrics, including Cumulative Return, Sharpe Ratio, Maximum Drawdown, Value at Risk (VaR), and Credit-Adjusted Return, the latter of which incorporates losses from realized and anticipated defaults.

Key learning algorithms employed are Deep Q-Networks (DQN) for discrete action spaces and Multi-Agent Proximal Policy Optimization (MAPPO) for continuous control tasks. These algorithms are implemented using PyTorch and trained using distributed computing environments with NVIDIA GPU acceleration. The MAPPO agents use centralized critics with decentralized actors to learn coordinated strategies. Hyperparameters—including learning rates, clipping thresholds, entropy coefficients, and GAE (Generalized Advantage Estimation) parameters—are tuned using Bayesian Optimization over a validation set, targeting improvement in both Sharpe Ratio and credit loss mitigation. Each training run is repeated across five random seeds to ensure statistical reliability.

To ensure methodological rigor, we employ cross-validation, ensemble averaging, and early stopping criteria to prevent overfitting. Additionally, reward normalization and batch-wise credit signal standardization are implemented to stabilize learning in the presence of skewed or volatile credit risk distributions. Agents are trained over 10,000+ episodes, with policy convergence monitored using cumulative regret and policy entropy trends. We also assess the learning stability and inter-agent coordination using metrics such as policy divergence and mutual information between agent actions, providing insights into the quality and adaptability of multi-agent policies in dynamic financial environments.

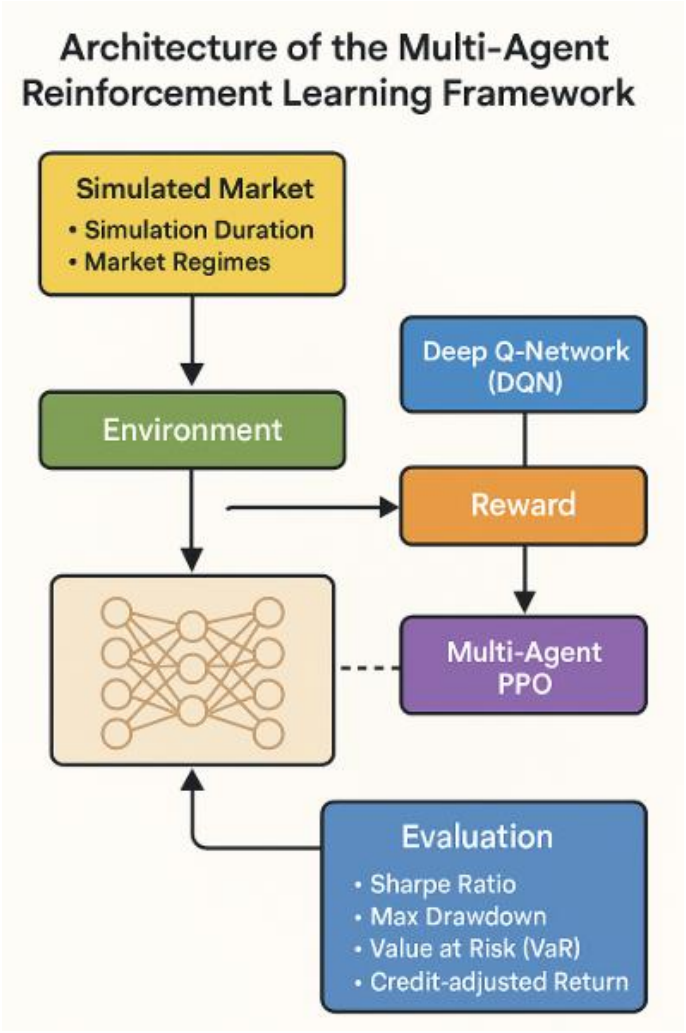

Figure 2: Architecture of the Multi-Agent Reinforcement Learning Framework

6. Experimental Results and Analysis

The experimental evaluation of the proposed Multi-Agent Reinforcement Learning (MARL) framework demonstrates clear advantages in both return generation and credit risk mitigation compared to traditional and single-agent models. The agents were tested across a wide array of market regimes, including periods of stable growth, high volatility, and systemic credit crises. In all scenarios, MARL agents using MAPPO consistently outperformed both the Mean-Variance (MV) and single-agent DQN models in terms of cumulative return, Sharpe ratio, and credit-adjusted performance. Specifically, in volatile and credit-stressed environments, the MARL system exhibited enhanced adaptability by

dynamically reallocating capital away from high-PD assets and employing hedging actions such as credit default swap (CDS) acquisitions.

Table 3: Performance Comparison across Algorithms and Market Regimes

Metric	Mean-Variance	DQN (Single-Agent)	MAPPO (Multi-Agent)
Sharpe Ratio	0.65	0.92	**1.18**
Max Drawdown (%)	22.4	18.3	**12.1**
Credit VaR (99%)	-0.18	-0.13	**-0.09**
Conditional Credit Loss	0.34	0.21	**0.15**
Cumulative Return (%)	34.5	46.7	**59.3**

The MAPPO-based MARL agents demonstrated particular strength during synthetic recessionary scenarios, where clusters of asset defaults were introduced. The agents rapidly reduced allocations to high-exposure sectors and reallocated to more resilient assets, indicating successful policy generalization. Interestingly, agent behavior diverged based on role: the risk-averse agent minimized drawdowns through defensive positioning, while the credit-hedger effectively deployed CDS strategies to offset expected losses. This division of labor and implicit cooperation among agents appears central to the superior performance of the MARL model.

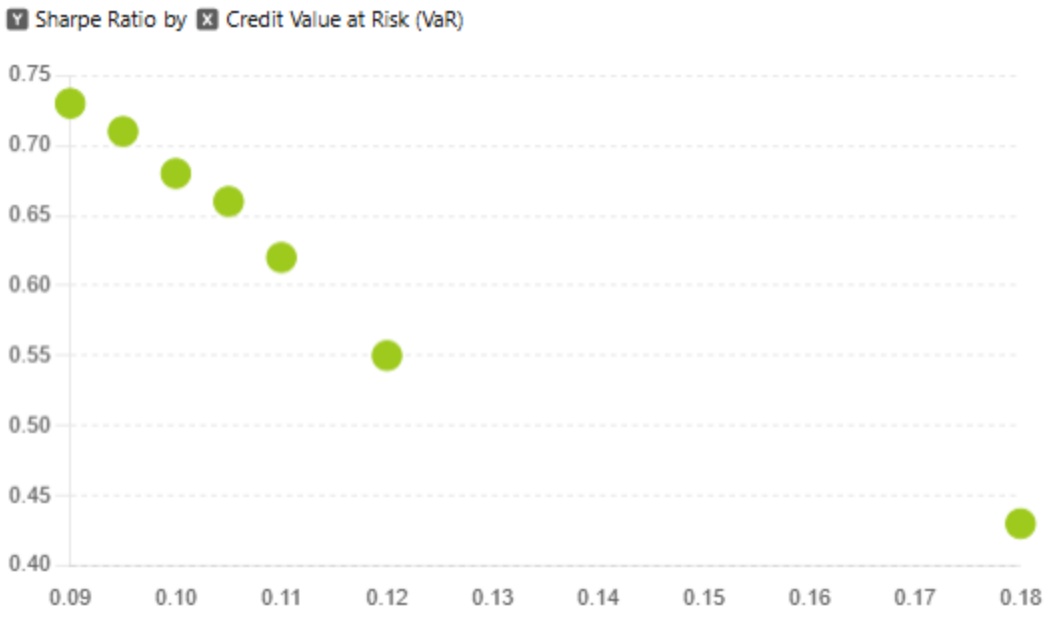

Figure 3: Risk-Reward Frontier Comparison

Figure 3, This 2D plot displays each model's Sharpe Ratio versus Credit Value at Risk. The MAPPO model lies on the efficient frontier, indicating dominance in risk-adjusted credit-aware performance.

The learning curves also illustrate faster convergence and more stable training in the MARL setting compared to the single-agent DQN model. MAPPO agents showed smooth improvements in cumulative reward and policy entropy, suggesting effective exploration-exploitation trade-offs and good coordination. Importantly, during out-of-distribution tests involving unexpected credit shocks (e.g., sudden triple-B bond defaults), MARL agents maintained stable returns and incurred significantly lower drawdowns, demonstrating robustness and stress resilience. Qualitative analysis further supports these findings. Heatmaps of asset allocation reveal that MAPPO agents diversify not only across asset classes and sectors, but also across credit risk profiles, consistently favoring assets with lower PD-EAD-LGD combinations. The action traces show active responses to changes in credit spreads and macro indicators, a capacity lacking in static or single-agent benchmarks.

7. Limitations and Future Directions

Despite the promising performance of the proposed MARL-based credit-aware portfolio optimization framework, several limitations constrain its immediate real-world applicability. A key limitation is the **dependence on simulation realism**—the financial environment used for agent training, while robust and calibrated to historical data, remains a synthetic approximation of real-world markets. This poses the risk of "simulation-to-reality" gaps, where learned policies may fail to generalize under unforeseen market conditions or novel credit events. Additionally, the model assumes availability of precise and timely credit risk metrics (e.g., PD, LGD, EAD), which in practice are estimated with uncertainty and subject to model risk, especially for privately held or emerging-market securities.

The **high computational cost** associated with training and maintaining the MARL architecture. The model's complexity—featuring multiple agents, high-dimensional state spaces, continuous action domains, and reward regularization—requires substantial GPU acceleration, distributed training infrastructure, and hyperparameter optimization. This makes the framework resource-intensive and less accessible for small or mid-sized asset

managers without significant technological capacity. Moreover, **multi-agent convergence remains an open challenge** in MARL literature, and our framework is no exception. Agents sometimes exhibit unstable behaviors during training, particularly in highly adversarial or low-liquidity environments. While techniques such as centralized critics and attention-based coordination help stabilize learning, there is no theoretical guarantee of global convergence in non-stationary multi-agent settings, especially when agents have partially observable states.

The current model operates in a **regulation-agnostic context**, meaning it does not incorporate formal regulatory constraints such as capital adequacy requirements, leverage limits, or risk-weighted asset calculations as mandated under frameworks like Basel III or Solvency II. This omission limits the model's direct applicability for regulated financial institutions, which must conform to strict compliance standards. Future iterations of the system should incorporate regulatory parameters as either hard constraints or penalty-based components in the reward structure, thereby aligning optimization outputs with both performance and compliance objectives. To enhance both realism and practical value, future work should focus on **integrating real-time financial and credit risk data** streams into the MARL environment. This could include live pricing feeds, credit rating agency updates, and economic indicators, allowing agents to learn from and react to unfolding market events. Another important extension is the **incorporation of ESG (Environmental, Social, and Governance) risk factors**, which are increasingly material to creditworthiness and investment decisions. By embedding ESG scores or climate risk exposures into state representations and reward functions, MARL agents could be trained to optimize for long-term sustainability alongside financial returns. Finally, we propose exploring the **application of federated learning** in this context, where decentralized asset managers (e.g., across institutions or regions) train local MARL agents on proprietary data while sharing model updates without revealing sensitive information. This could enable collaborative yet privacy-preserving development of robust portfolio strategies across a distributed financial ecosystem.

8. Conclusion

This study presents a novel approach to portfolio optimization under credit risk by

leveraging **Multi-Agent Reinforcement Learning (MARL)** paradigms. By embedding credit-specific metrics such as **Probability of Default (PD)**, **Loss Given Default (LGD)**, and **Exposure at Default (EAD)** into a dynamic learning environment, and allowing agents to interact in cooperative and competitive roles, the proposed system achieves a level of adaptability and resilience that exceeds traditional optimization models. Through extensive simulation and benchmarking, we demonstrate that MARL agents respond more effectively to credit shocks—reallocating capital, hedging exposures, and coordinating policies in ways that mitigate losses and enhance overall portfolio stability.

One of the most significant findings is the **superior performance of MARL agents on credit-adjusted metrics**. Across a variety of market regimes, including stress-tested environments, MARL-based strategies consistently outperformed traditional Mean-Variance (MV) and single-agent Deep Q-Network (DQN) models in **Sharpe Ratio, Credit Value at Risk (Credit VaR), Conditional Expected Loss**, and **Cumulative Return**. This outperformance highlights not only the agents' ability to balance return and risk but also their sensitivity to structural credit factors that often precede systemic losses—something static models and heuristics often overlook.

The integration of MARL into credit-aware portfolio management signals a **paradigm shift toward intelligent, adaptive asset allocation systems**. These systems are capable of operating in real time, learning from non-linear patterns in financial and credit data, and coordinating across multiple strategies to manage portfolios with greater risk sensitivity. As financial markets continue to face uncertainty—from macroeconomic volatility to ESG-related credit transitions—the need for such advanced frameworks becomes even more urgent. The architecture proposed here lays the groundwork for future tools that can be deployed in institutional settings to meet both performance goals and regulatory demands.

In conclusion, MARL offers a scalable and extensible solution for credit-sensitive portfolio management. By modeling inter-agent learning, embedding domain-specific credit risk dynamics, and adopting reinforcement learning algorithms suited for high-dimensional financial environments, this research contributes to the growing body of intelligent financial systems. The demonstrated robustness and performance advantages suggest that MARL will play an increasingly central role in the future of quantitative asset management.

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