MATH/IDS 789 Project Report

Caleb Carlyle, Fernando Villegas , Leo Yao, and Xinkai Yuan

1 Technical Project

1.1 Introduction - Perpetual Futures and Funding Rate Arbitrage

Economist Robert J. Shiller first introduced perpetual futures contracts—perps for short—in 1993. Like futures, perps are derivatives that allow traders to speculate on the price movements of an asset, without actually owning the asset itself. As opposed to traditional futures, perps do not have an expiration date, so traders can hold their positions indefinitely, as long they do not run out of money. On their inception, the idea was to have a way to facilitate price discovery—that is, to determine the fair price of an asset via market processes—for illiquid or hard-to-price assests, such as a house that generates rents as cash-flow. Nowadays, perpetual futures have become a popular derivative in cryptocurrency markets.

The market dynamics do not necessarily guarantee that perpetual futures prices should remain close to the spot price. For regular futures, the maturity date provides a natural force that makes the futures price converge to the spot. Since perps do not expire, one minimizes the deviations from the futures price to the spot via periodic funding payments between the long and short positions, usually every eight hours on most crypto exchanges. The funding payments are computed as the sum of a premium term, obtained from the difference in the future and spot price, plus an interest rate term, usually set by the exchange. One should intuitively think that the rate is positive when the future price exceeds the spot, and negative when the future price is below the spot. When the funding rate is positive, the longs make payments to the shorts, discouraging traders from opening more long positions, driving the futures price lower, closer to the spot. The situation is reversed when the rate is negative: the shorts make payments to the longs, discouraging short positions.

The funding mechanism opens the possibility for a trading strategy that exploits the funding payments while undertaking minimal market-risk. For instance, if the funding rate for a specific coin is positive, we may open a short position in the perp market and simultaneously open a long position in the spot market for that same coin. Opening both positions hedges the market risk, and we earn a profit from the funding payments the longs make while the funding rate is positive. If the funding rate is negative, the situation reverses but the logic is the same: we open a long position in the perp market and a short position in the spot, and we earn a profit from the funding payments the shorts in the perp market make. We refer to this strategy as funding rate arbitrage. Despite the relatively risk-free nature of the strategy, traders still need to make the right decision at the right time and execute their trades correctly. Our project seeks to evaluate the performance of an AI agent in predicting the movements of the funding rate to accurately open positions that present an arbitrage opportunity.

2 Market Simulation

Historical funding rate data requires paid API access (e.g., CoinGecko Pro), so instead we decided to simulate market data using real market statistics and theoretical models to validate the strategy. There are three things to model: the spot price, the funding rate and the perp price.

2.1 Modeling the Spot Price

We use Geometric Brownian Motion to model the spot price S_t for each asset, since it is one of the usual ways to model the change of the price of stocks using a drift and a volatility parameters [9]. The stochastic differential equation is:

$$dS_t = (r_a - r_b)S_t\,dt + \sigma S_t\,dW_t \tag{1}$$

where $r_a = 5\%$ is the annual USD lending rate, $r_b = 0\%$ is the crypto staking yield, and $\sigma \in [0.8\%, 1.5\%]$ per 8-hour period, corresponding to annualized volatility of approximately 26%–50%, consistent with observed Bitcoin volatility which averages around 54% annually [10]. The drift term $r_a - r_b$ can be thought of as the interest rate spread between the USD (or more accurately, a stablecoin a equivalent to the USD) and a cryptocurrency b.

2.2 Modeling the Funding Rate and Pricing Perpetual Futures

Next we model the funding rate, which we will then use to price the perpetual futures, following the work of Ackerer et al. [2]. Funding payments have a simple structure: the funding payment F_t at time t equals:

$$F_t = \left(\kappa_t \frac{P_t^{\text{perp}} - S_t}{S_t} + \iota_t \right) S_t \tag{2}$$

where S_t is the spot price, κ_t is the rate "controlling the strength of the anchoring of the futures price to the spot price", and ι_t is some interest rate set by the exchange at time t. We define the funding rate f_t at time t to be

$$f_t = \kappa_t \frac{P_t^{\text{perp}} - S_t}{S_t} + \iota_t. \tag{3}$$

Ackerer et al., as well as He et al., have found formulas to price perpetual futures under no-arbitrage assumptions, finding equilibrium prices that converge to the spot prices under appropriate hypotheses [2, 16]. One observation from both papers is that the premium component of the rate involving κ_t is meant to be a correction mechanism similar to mean reversion, keeping the price of the perpetual close to the spot [2].

For this reason, we model funding rates using an Ornstein-Uhlenbeck (OU) process, which exhibits mean-reverting behavior and is widely used in finance to model interest rates [21]. According to industry reports, average funding rates range from 0.015% to 0.02% per 8-hour period, with the average annualized return from funding rate arbitrage at 14.39% in 2024 and 19.26% in early 2025 [15]. We use $\bar{f} = 0.02\%$ per 8 hours (approximately 21.9% annualized) to represent moderately bullish market conditions. The stochastic differential equation is:

$$df_t = \theta(\bar{f} - f_t)\, dt + \sigma_f \, dW_t \tag{4}$$

where $\bar{f} = 0.02\%$ is the mean funding rate, $\theta = 0.15$ is the mean-reversion speed, and $\sigma_f = 0.01\%$ is the funding rate volatility.

The mean-reversion speed $\theta = 0.15$ per 8-hour period corresponds to a half-life of $t_{1/2} = \ln(2)/\theta \approx 4.6$ periods, or approximately 1.5 days. This implies that deviations from the mean funding rate decay by half within 1.5 days, consistent with observed short-term persistence of funding rate fluctuations. The volatility parameter $\sigma_f = 0.01\%$ is chosen such that funding rates typically remain within the range $[0.01\%, 0.03\%]$ (one standard deviation around the mean), matching empirical observations.

We incorporate asset-specific characteristics observed in real markets: altcoins like DOGE and SOL typically exhibit higher funding rates due to greater speculative activity, while BTC tends to have lower, more stable rates. Specifically:

$$\bar{f}_{\text{sym}} = \begin{cases} 1.3 \times \bar{f} & \text{if sym} \in \{\text{DOGE}, \text{SOL}\} \\ 0.9 \times \bar{f} & \text{if sym} = \text{BTC} \\ \bar{f} & \text{otherwise} \end{cases} \tag{5}$$

where $\bar{f} = 0.02\%$ per 8 hours is the baseline mean.

Exchanges impose limits on funding rates to prevent extreme values during volatile markets. On Binance, the funding rate formula includes a clamp on the premium component: Premium $=$ clamp(Premium, $-0.05\%, +0.05\%$), while the interest rate component is fixed at 0.01% per 8 hours [5, 16]. For contracts with maximum leverage of 25x or below, the total capped funding rate is $\pm 3\%$ per 8-hour period [4]. In our simulation, we use a conservative clamp of $\pm 0.75\%$, which is sufficient to capture normal and moderately volatile market conditions while remaining well within exchange limits.

We take inspiration from the theoretical formulas to simplify our model. In particular, we assume $\iota = r_a - r_b$, the interest rate spread between currency a (USD, or a stablecoin equivalent) and currency b (the cryptocurrency), is constant. Intuitively, if $\iota > 0$, the low interest on currency b makes it less attractive to hold, so the futures contract is more appealing, contributing positively to the funding rate. Conversely, if $\iota < 0$, the high interest rate on b makes holding the cryptocurrency more attractive, contributing negatively to the funding rate. For simplicity, we also assume r_a, r_b, and the anchoring rate κ are constant.

Finally, we price perpetual futures by solving from the funding rate equation:

$$P_t^{\text{perp}} = S_t \left(1 + \frac{f_t - \iota}{\kappa}\right) = S_t \left(1 + \frac{f_t - (r_a - r_b)}{\kappa}\right) \tag{6}$$

We call the quantity $b_t = \frac{f_t - \iota}{\kappa}$ the basis.

2.3 Expected Returns

With mean funding rate $\bar{f} = 0.02\%$ per 8-hour period and three funding periods per day, the expected annualized return before costs is:

$$\mathbb{E}[r_{\text{annual}}] = \bar{f} \times 3 \times 365 = 0.02\% \times 1095 \approx 21.9\% \tag{7}$$

After accounting for entry costs of approximately 0.115% (spot fee 0.075% plus perpetual fee 0.04%), the net expected return remains attractive for positions held over multiple weeks.

3 AI Agent

We integrate a large language model (LLM) as the decision-making agent in our trading system. The agent is invoked every 8-hour funding period to analyze current market conditions and determine optimal position management. Access to the Python code can be found here.

3.1 Model Selection

We use **Doubao** , a large language model developed by ByteDance, accessed via the Volcano Engine API with model identifier `doubao-1-5-lite-32k-250115`. We choose Doubao for the significantly lower API costs compared to other models such as GPT-4 or Claude, which matters when the agent is invoked 90 times during a 30-day backtest. Moreover, its OpenAI-compatible interface enables straightforward integration.

The agent essentially serves as a portfolio manager that receives current funding rates for all tracked assets (BTC, ETH, BNB, DOGE, SOL), analyzes arbitrage opportunities, decides position actions (open, hold, close, or reverse), selects which assets to include, and determines capital allocation weights.

3.2 Prompt Design

The prompt consists of a system message and a user message. The system message educates the agent about the AHJ [2] theoretical framework, including: the funding rate mechanism ($f_t = \kappa \cdot b_t + (r_a - r_b)$), delta-neutral arbitrage logic (short perp when funding is positive, long perp when negative), the insight that higher $|f|$ represents better opportunities, and risk considerations such as funding rate reversals.

The user message provides current market state: funding rates for each asset (sorted by magnitude), aggregate statistics (average and maximum), current position context (direction, assets, allocations), and transaction costs (0.115%). The agent returns a JSON response containing action, direction, selected assets, allocation weights, confidence score, and reasoning.

3.3 Decision Rules and Hyperparameters

The agent's decisions follow principles from AHJ (2024). For direction, short_perp is chosen when $f_t > 0$ and long_perp when $f_t < 0$. For asset selection, the agent chooses 2–4 assets with highest $|f_t|$, filtering those below 0.005%. Capital is allocated proportionally to funding rate magnitude: $w_i = |f_i| / \sum_j |f_j|$. Position reversal occurs only when $|f_t| > 0.01\%$ in the opposite direction, avoiding unnecessary costs from weak signals.

Key hyperparameters include: temperature of 0.2 for consistent decisions, confidence threshold of 0.3 for position entry, minimum funding rate of 0.005% for asset inclusion, and reversal threshold of 0.01%.

4 Experimental Setup

We design a backtest framework to evaluate the delta-neutral funding rate arbitrage strategy over a 30-day simulation period. This section describes the experimental configuration, execution pipeline, and evaluation metrics.

4.1 Configuration

The backtest simulates 30 days of trading with 3 funding periods per day (every 8 hours), yielding 90 decision points. We track 5 major cryptocurrencies: BTC, ETH, BNB, DOGE, and SOL, selected for their high liquidity and active perpetual futures markets. The initial capital is $10,000, with 80% deployed in positions and 1x leverage (no leverage) to match conservative arbitrage fund practices.

Transaction costs follow Binance VIP0 rates. For spot trading, the base fee is 0.1%, reduced to 0.075% with the 25% BNB discount [7]. For perpetual futures, VIP0 users pay 0.02% maker fee and 0.05% taker fee [6]; we use 0.04% as a blended average assuming a mix of maker and taker orders. The total entry cost is therefore 0.075% + 0.04% = 0.115% per position. Funding rates are simulated with mean 0.02% per 8 hours (approximately 21.9% annualized), representing moderately bullish market conditions consistent with early 2025 averages [15]. Recall we incorporated the asset-specific characteristics from (5).

4.2 Execution Pipeline

Each 8-hour period proceeds through four stages:

Stage 1: Market Data Generation. The simulation generates current funding rates for all assets using the OU process. Each asset's rate mean-reverts toward its equilibrium level (higher for altcoins like DOGE and SOL, lower for BTC), with random shocks introducing period-to-period variation.

Stage 2: AI Agent Decision. The Doubao agent receives current funding rates, position state, and cost parameters. It analyzes the market and returns a structured decision: action (open/hold/close/reverse), direction (short_perp/long_perp), selected assets, allocation weights, confidence score, and reasoning. The agent is called every period, enabling dynamic portfolio adjustment.

Stage 3: Strategy Execution. The strategy module executes the agent's decision subject to validation. Positions are opened only when confidence exceeds 0.3. For "open" actions, capital is allocated across selected assets according to the specified weights. For "hold" actions, funding income is collected based on current rates and position values. For "reverse" actions, the existing position is closed (incurring exit costs) and a new position opened in the opposite direction.

Stage 4: State Update and Logging. Portfolio state is updated: funding income added, transaction costs deducted, and equity recalculated. Comprehensive logs record the period's funding rates, agent decision (including reasoning), executed action, position details, P&L breakdown, and cumulative equity.

4.3 Recorded Metrics

We record the following metrics throughout the backtest:

Per-Period Metrics: funding rates for each asset, average funding rate, agent's action and reasoning, position direction and value, selected assets and allocations, funding income, transaction costs, and net P&L.

Aggregate Metrics: total return, final equity, Sharpe ratio (annualized), maximum drawdown, win rate (percentage of profitable periods), total funding collected, total costs incurred, and average realized funding rate.

The Sharpe ratio is computed as:

$$\text{Sharpe} = \frac{\bar{r}}{\sigma_r} \times \sqrt{N} \tag{8}$$

where $\bar{r}$ is mean period return, σ_r is return standard deviation, and $N = 1095$ is the number of periods per year.

Maximum drawdown measures the largest peak-to-trough decline:

$$\text{MDD} = \max_t \frac{\text{Peak}_t - \text{Equity}_t}{\text{Peak}_t} \tag{9}$$

4.4 AI Agent Integration

The AI agent participates in every trading decision, distinguishing our approach from static rule-based strategies. Each period, the agent observes the complete market state and can dynamically adjust:

- **Asset Selection:** The agent identifies which assets currently offer the best risk-adjusted returns, potentially shifting allocation as funding rates evolve. For example, if DOGE funding drops while SOL funding rises, the agent can reallocate accordingly.
- **Position Timing:** The agent determines when to enter, exit, or reverse positions based on funding rate magnitude and direction, balancing expected income against transaction costs.
- **Confidence-Gated Execution:** Low-confidence decisions (below 0.3) are not executed, preventing the strategy from acting on ambiguous signals.

This per-period decision-making enables the strategy to adapt to changing market conditions rather than following fixed rules, while the theoretical grounding fed to the agent ensures decisions remain economically principled.

5 Results

Figure 1 presents the backtest results over 30 days (90 funding periods) with $10,000 initial capital.

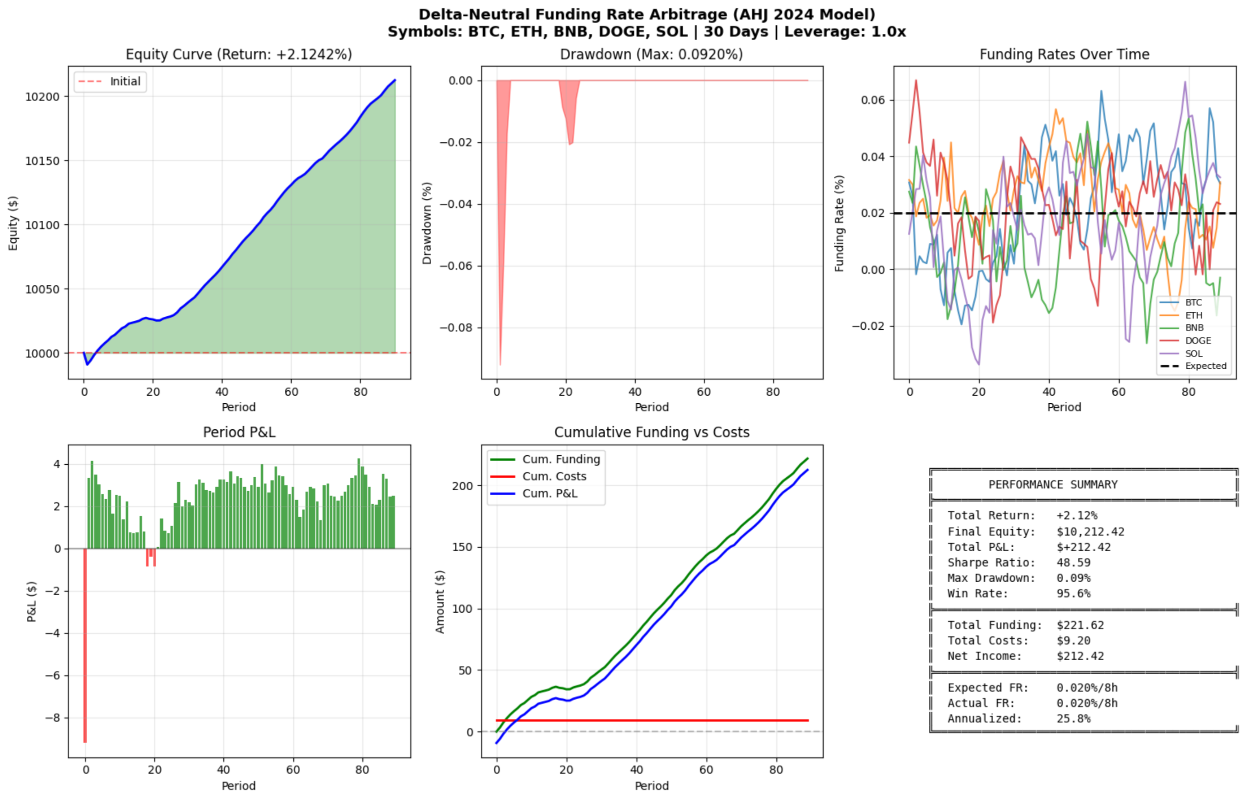

Figure 1: Backtest results for delta-neutral funding rate arbitrage. Top row: equity curve, drawdown, and funding rates over time. Bottom row: period P&L, cumulative funding vs costs, and performance summary.

5.1 Overall Performance

The strategy achieves a total return of +2.12%, growing initial capital from \$10,000 to \$10,212.42. Annualized, this corresponds to approximately 25.8%, which aligns with empirical funding rate arbitrage returns reported in 2024 market studies (14–26% annual). The Sharpe ratio of 48.59 indicates exceptional risk-adjusted performance, reflecting the low-volatility nature of delta-neutral strategies.

5.2 Risk Profile

The maximum drawdown is remarkably low at 0.09%, occurring during the initial position entry when transaction costs are incurred before funding income accumulates. The equity curve shows steady, near-monotonic growth after the first few periods, characteristic of successful carry strategies. The win rate of 95.6% confirms that the vast majority of periods generate positive P&L once the position is established.

5.3 Funding Income Analysis

Total funding income over 30 days amounts to \$221.62, while total transaction costs are only \$9.20, yielding net income of \$212.42. The cost-to-income ratio of 4.2% demonstrates that transaction costs are well-amortized over the holding period. The average realized funding rate of 0.020% per 8 hours matches the expected rate from our simulation calibration, validating the market model.

The cumulative funding vs. costs panel shows that costs are incurred upfront (position entry) while funding accumulates linearly over time. Break-even occurs within the first few periods, after which all funding income contributes to profit.

5.4 Funding Rate Dynamics

The funding rates panel reveals mean-reverting behavior around the 0.02% expected level (dashed line). Individual assets exhibit characteristic patterns: altcoins (DOGE, SOL) show higher volatility and occasional spikes above 0.05%, while BTC maintains more stable rates. The AI agent exploits these dynamics by overweighting high-funding assets when opportunities arise.

5.5 Period P&L Distribution

The period P&L histogram shows predominantly positive values ($2–4 per period) with few negative periods. The large negative spike at period 0 reflects the initial entry cost of approximately $9.20. Subsequent small negative periods occur during position reversals when funding direction temporarily flips. The consistency of positive periods validates the strategy's core premise: delta-neutral positions reliably capture funding income.

6 Conclusion

We present a delta-neutral funding rate arbitrage system that integrates large language model decision-making with theoretical foundations from AHJ (2024). Our approach demonstrates that LLM agents can effectively manage quantitative trading strategies when provided with appropriate theoretical grounding and structured market data.

The backtest results validate the strategy's viability: a 2.12% return over 30 days (25.8% annualized) with Sharpe ratio of 48.59 and maximum drawdown of only 0.09%. These metrics align with empirical reports of funding rate arbitrage performance in 2024 markets, confirming that our simulation is realistically calibrated.

Three key insights emerge from this work. First, the integration of academic theory into LLM prompts significantly improves decision quality. By educating the agent about funding rate mechanics, optimal allocation principles, and risk considerations from AHJ (2024), we enable informed rather than naive decisions. Second, per-period agent invocation allows dynamic adaptation to changing market conditions, particularly in reallocating capital toward assets with temporarily elevated funding rates. Third, the strategy's profitability depends critically on realistic parameter calibration—our initial implementation with theoretical equilibrium rates (0.01% per 8h) underperformed, while calibration to actual 2024 market data (0.02% per 8h) produced returns consistent with industry benchmarks.

Several limitations warrant discussion. Our backtest uses simulated rather than historical data, which may not capture tail events or correlation structures present in real markets. The strategy assumes perfect execution at quoted prices without slippage or liquidity constraints. Additionally, the LLM's decisions, while theoretically grounded, may exhibit inconsistencies across different market regimes not represented in training data.

Future work could extend this framework in several directions: backtesting on historical funding rate data from exchange APIs, incorporating execution costs and slippage models, expanding to a larger asset universe, and comparing different LLM architectures and prompting strategies. The integration of reinforcement learning to fine-tune the agent's decision thresholds based on realized performance presents another promising avenue.

7 Non-Technical Project

7.1 Introduction

This report provides a comprehensive operational and quantitative analysis of Coinbase, the leading publicly traded cryptocurrency exchange in the United States. The objective is to dissect the unique market microstructure of the digital asset economy and contrast it with traditional financial institutions, which have been the primary focus of this semester's studies. As of late 2025, the cryptocurrency landscape has shifted from a retail-driven speculative craze to a regulated institutional asset class. Many of the initial criticisms of cryptocurrency have been managed as time has permitted refinement of the complex landscape of a new asset class. This maturation is driven by the global adoption of stablecoin regulations and the integration of spot crypto ETFs into standard brokerage portfolios. What was once an ecosystem that could easily be written off as a fleeting trend, has grown into a much more legitimate and complex counterpart to traditional finance.

However, despite this convergence, the underlying mechanics of crypto markets remain fundamentally distinct from traditional equities. While the New York Stock Exchange (NYSE) operates on a centralized matching engine with fixed hours and $t+1$ settlement cycles, crypto markets operate on atomic settlement, continuous trading, and a fragmented global liquidity landscape [14]. This report serves to examine the specific quantitative roles within this ecosystem. By contrasting these roles with their more traditional counterparts, we aim to provide Duke University graduate students, from Data Science, Computer Science, Mathematics, and related departments, with a strategic outline for bridging the gap between academic theory and the specific demands of the modern crypto-economy. Coinbase is selected as a guide through this process, in order to provide concrete examples of careers and the current demand for various skills.

The current United States job market has grown increasingly difficult to navigate due to economic factors, but technology-focused careers have been additionally impacted by the rise of Large Language Models (LLMs). As such, it is especially important for students to understand the skills that are required to be successful, particularly in the early career technical jobs that have been heavily impacted by LLMs. This includes understanding the skills that are not easily replaced by technology, providing insight into the best areas to develop, providing improved leverage in the job search.

7.2 Coinbase Overview

Coinbase operates as a vertically integrated financial infrastructure provider, meaning the product supply chain is under the control of the company. In the traditional financial world, the roles of broker, exchange, and custodian are legally separated to prevent conflicts of interest. Coinbase effectively collapses these three distinct functions into a single entity. Clients interact directly with the platform to trade, clear, and settle assets instantly. This changes the scope of functions and needs for the organization, especially in terms of complex functionality within the company.

7.2.1 Business Model Transition

Historically, Coinbase's revenue was heavily correlated with the volatility of Bitcoin, derived primarily from transaction fees. However, in 2025, the company successfully pivoted toward a "Subscription and Services" model. This includes revenue from *Coinbase One* (retail subscriptions), custodial fees for ETF issuers (Coinbase Prime), and significant interest income generated from the reserves backing USDC (USD Coin) [12]. The company's strategic vision has expanded to "The Everything Exchange," aiming to offer tokenized real-world assets (RWAs) alongside native crypto assets, effectively bringing traditional securities onto blockchain infrastructure [19]. This transition has enabled a more sustainable business model, even without the same institutional power held by traditional financial institutions. The pivot has made Coinbase a much more viable career path, even for early career workers who are trying to build their own skills and resumes.

7.2.2 Key Products and Structure

Coinbase's ecosystem is anchored by three primary verticals that diversify its revenue beyond simple retail transaction fees. For institutional clients, **Coinbase Prime** serves as a comprehensive prime brokerage platform used by hedge funds and asset managers. It utilizes "Smart Order Routing" (SOR) to execute large block trades across fragmented liquidity venues without signaling intent to the wider market, a major difference from traditional finance that regulates to avoid this fragmentation. Geographically, the company expands its reach through the **Coinbase International Exchange**, a platform catering to foreign clients that offers perpetual futures. These derivatives, which do not exist in traditional US equities markets, allow for high-leverage hedging strategies that are essential for sophisticated traders. Finally, the company has evolved from a venue operator to a protocol developer with the launch of **Base**, an Ethereum Layer-2 blockchain. This strategic shift allows Coinbase to capture fees directly from the decentralized finance (DeFi) activity occurring on their own network infrastructure, effectively integrating the exchange with the on-chain economy.

7.3 Relevant Roles

The following role descriptions are adapted from current job postings on Coinbase's careers page.[1]

7.3.1 Quantitative Trader

Major Purpose:
At Coinbase, the "Quantitative Trader" role is often situated within *Coinbase Execution Services*. Unlike a proprietary trader at a hedge fund whose goal is to generate alpha (profit) by taking directional risks, a Coinbase quant trader acts as an agent. Their primary mandate is *Liquidity Provision* and *Best Execution*. They ensure that when an institutional client wants to buy $50 million of Bitcoin, for example, the order is executed efficiently without causing massive price slippage.

Day-to-Day Tasks:
A typical day involves managing the algorithmic routing engines that split large "parent" orders into thousands of smaller "child" orders across various liquidity venues (including competitors like Binance or Kraken). Traders use Python and C++ to optimize these "Smart Order Routers" (SORs). They constantly monitor "inventory risk", holding temporary positions of assets to facilitate client trades, and auto-hedge these exposures using derivatives. They also analyze market microstructure data to adjust quote spreads based on real-time volatility regimes.

Difference in Crypto vs. Traditional:
The most significant operational difference for traders in traditional markets and crypto markets, is the 24/7/365 nature of the market. There is no "market close" to reconcile books, so algorithms must run continuously without downtime. Additionally, crypto liquidity is highly fragmented. In traditional institutions, Regulation NMS ensures a National Best Bid and Offer (NBBO). In crypto, the price of Bitcoin can diverge significantly between

[1] Role descriptions and skill requirements from [11].

exchanges, requiring traders to write complex arbitrage logic to source the best price globally. This is where the age of cryptocurrency is evident, because its birth during the internet age has permitted greater complexity than the traditional systems. The mix of these two factors adds a great deal of intricacy to effective trading.

7.3.2 Exchange Product Manager

Major Purpose:

The Exchange Product Manager (PM) acts as the technical owner of specific trading products, such as the Matching Engine, APIs, or Derivatives platform. Their goal is to build a trading venue that is robust enough for high-frequency trading (HFT) firms yet accessible enough for retail users. They bridge the gap between business strategy (revenue) and engineering reality (latency). The physical reality of worldwide exchange is that theoretical truths cannot always be implemented at scale, or not without loss, so an Exchange PM must facilitate the realization of the theoretical outlines by evaluating tradeoffs in different approaches.

Day-to-Day Tasks:

An Exchange PM works heavily with data. They query SQL databases to analyze "fill rates", how well the company fills the clients' needs, and "API latency", execution speeds, to ensure Coinbase remains competitive with offshore exchanges. They write Product Requirement Documents (PRDs) for new features, such as "Portfolio Margin" accounts, which allow clients to use unrealized profits in one asset as collateral for another. They must also coordinate with legal teams to ensure new token listings comply with the evolving regulatory framework, like determining if a new token is a security or a commodity.

Difference in Crypto vs. Traditional:

In traditional finance, market structures change at a very slow pace. In crypto, a PM must adapt to rapid protocol changes as the ecosystem is constantly evolving with new technologies, market behaviors, and regulations. For example, if the Ethereum network undergoes a major upgrade (a "hard fork"), the PM must ensure the exchange's deposit/withdrawal engines are updated to handle the new technical standards. This requires a level of "protocol literacy" that is non-existent in traditional equity product management.

7.3.3 Machine Learning Engineer: Risk

Major Purpose:

The Machine Learning Engineer with a risk focus serves as the operational backbone of

Coinbase's "Trust and Safety" infrastructure. The primary objective of this role is the real-time detection and prevention of financial crimes, specifically money laundering, fraud, and account takeovers (ATO). This mission is critical because, unlike traditional credit card transactions which can be reversed, cryptocurrency transfers are immutable; once funds leave the platform, they cannot be clawed back. This is a feature of the blockchain technology that is at the heart of cryptocurrency. Consequently, these engineers are tasked with building and deploying large-scale classification models using deep learning frameworks like PyTorch or TensorFlow. Like PMs, these engineers must be constantly learning as the space evolves in order to effectively manage risks and threats.

Day-to-Day Tasks:

Their day-to-day work relies heavily on feature engineering from two distinct data sources. They analyze "off-chain" data—such as device fingerprints, login velocity, IP geolocation, and behavioral biometrics to establish user identity patterns. Simultaneously, they leverage "on-chain" data using Graph Neural Networks (GNNs) to map the transaction history of destination wallets, flagging high-risk interactions with sanctioned entities or obfuscation services like Tornado Cash.

Difference in Crypto vs. Traditional:

The adversarial nature of crypto fraud is significantly higher. Attackers use sophisticated "smart contract exploits" and "dusting attacks" (sending tiny amounts of crypto to thousands of wallets to de-anonymize them). Traditional bank fraud models, which rely on static identity data (KYC), fail against these dynamic, pseudonymous threats. A crypto ML engineer must be part data scientist, part cybersecurity analyst, especially as threats become more sophisticated.

7.3.4 Risk Manager

Major Purpose:

The Risk Manager oversees the aggregate financial solvency of the exchange, essentially ensuring that the exchange can meet its obligations under a variety of market scenarios. They focus on two critical pillars: *Counterparty Credit Risk* (ensuring institutional clients have enough collateral to cover their leverage) and *Liquidity Risk* (ensuring Coinbase has enough liquid assets in "hot wallets" to satisfy sudden mass withdrawals). This role needs to consider various risks from a strong basis in probability theory to accurately quantify risk.

Day-to-Day Tasks:

Risk Managers build stress-test scenarios using Monte Carlo simulations: "What happens to our collateral value if Bitcoin drops 50% in one hour?" They design and monitor the "Liquidation Engine," an automated system that forcibly closes client positions when their margin falls below maintenance requirements. They also manage "staking risk," ensuring that assets locked in staking protocols are not subject to "slashing" (penalties for network downtime). Their testing and simulations must be rigorously developed and tested before implementation, in order to ensure they are robust to real market conditions and can hold up beyond simulation or back-testing.

Difference in Crypto vs. Traditional:
In traditional finance, risk models (like Value-at-Risk) often assume normal distributions or historical mean reversion. Crypto assets exhibit "fat tails" and extreme kurtosis, showing that "rare" events are not actually all that rare. A crypto Risk Manager cannot rely on standard Gaussian models and must invent novel frameworks that account for unique risks like stablecoin de-pegging or smart contract hacks. This is where a deeper understanding of statistical modeling is vital, because careless modeling assumptions can have significant consequences in model output, and as a consequence, decision-making.

7.4 Relevant Skills and Gap Analysis

7.4.1 Quant Trader

For the Quant Trader role, technical proficiency is anchored in a dual-language approach: C++ is required for building low-latency execution systems, while Python (specifically Pandas and NumPy) is essential for strategy research. Candidates must also possess a deep understanding of order book dynamics—navigating Level 1, 2, and 3 data, along with slippage modeling and the management of real-time WebSocket APIs. The Duke course catalog aligns well with these requirements; *MATH 585: Algorithmic Trading* covers the specific back-testing and strategy optimization workflows used in trading roles, while *MATH 581: Mathematical Finance* provides the necessary theoretical foundation for pricing complex derivatives. However, a significant educational gap exists regarding Decentralized Finance Literacy. While university coursework focuses on Central Limit Order Books (CLOBs), modern crypto trading heavily utilizes Automated Market Makers (AMMs) like Uniswap. Consequently, critical concepts such as "Impermanent Loss" and "MEV" (Maximal Extractable Value) are more complex and specific to crypto, making them topics that require independent study.

7.4.2 Exchange Product Manager

The technical requirements for an Exchange Product Manager are stringent, with SQL fluency being a non-negotiable baseline for data-driven decision making. Beyond querying data, candidates must possess a working knowledge of API standards—specifically REST, FIX, and WebSockets, and grasp fundamental distributed systems concepts such as latency, throughput, and consensus mechanisms. Duke's academic offerings provide environments to develop these skills; *FINTECH 513: FinTech Product Development* directly addresses the lifecycle of financial software, while *IDS 706: Data Engineering* provides the cloud infrastructure and data pipeline knowledge necessary to effectively converse with engineering teams. However, a distinct gap remains regarding **Blockchain Architecture**. A Product Manager at Coinbase must understand the nuanced trade-offs that are induced by product implementation. This technical understanding, which dictates product feasibility, is rarely covered in standard curricula and is typically acquired through self-directed study. A candidate needs to show depth of understanding of crypto markets, which is unlikely to be acquired in a classroom setting alone.

7.4.3 Machine Learning Engineer - Risk

To succeed as a Machine Learning Engineer in Risk, candidates require a sophisticated technical toolkit that extends beyond standard data science. Proficiency in Deep Learning and Graph Neural Networks (GNNs) is essential for modeling complex transaction relationships, while expertise in MLOps pipelines (such as Kubeflow or Airflow) and real-time inference optimization ensures these models function at scale. Duke's curriculum provides strong theoretical support for this role; *IDS 599: AI in Finance* specifically applies machine learning techniques to financial datasets, and *COMPSCI 671: Machine Learning* offers the rigorous theoretical depth needed to build custom architectures. However, the primary educational gap lies in **On-Chain Forensics**. While academic courses typically utilize clean, structured CSV files, crypto risk analysis requires parsing raw, hex-encoded data directly from blockchain nodes via RPC calls. Learning how to "index" a blockchain to extract usable features is a specialized data engineering skill that is rarely covered in general machine learning. However, the topics learned in these classes are a well-aligned precursor to learning the specialized data skills that Coinbase wants.

7.4.4 Risk Manager

The Risk Manager role demands a rigorous quantitative foundation, specifically in stochastic calculus, Monte Carlo simulation, and derivatives pricing models such as Black-Scholes adjustments, alongside necessary data skills like SQL. Duke's curriculum offers exceptional alignment for this career path; *IDS/MATH 583: Risk Management & Derivatives* serves as the cornerstone, covering essential concepts like VaR and stress testing, while *ECON 590: Financial Econometrics (Ocassionally offered special topics course)* provides the necessary tools for modeling the time-series volatility characteristic of crypto assets. However, a critical professional gap exists in **Smart Contract Auditing**. Unlike a traditional risk manager who assesses financial ratios, a crypto risk manager must essentially assess code quality. If a collateral asset is built on buggy code, its value can plummet to zero instantly, creating a unique intersection of software auditing and financial risk that is not typically addressed in standard quantitative finance programs.

7.5 Conclusion

The analysis of Coinbase reveals a professional environment that is operationally similar to traditional finance—relying on Python scripts, stochastic modeling, and SQL queries—but philosophically and structurally divergent. Transitioning from the academic rigor of Duke University to the dynamic ecosystem of Coinbase requires a fundamental shift in mindset from static optimization to dynamic resilience. While the "crypto winter" of previous years has thawed into the regulated institutional landscape of 2025, the core engineering challenges remain unique. The market's continuous nature, atomic settlement, and fragmentation demand that employees possess not just technical fluency, but a high degree of operational vigilance that is rarely required in the *t+1* settlement world of traditional equity markets.

Furthermore, in a job market where Large Language Models (LLMs) are rapidly simplifying entry-level software engineering and data analysis tasks, the roles at Coinbase offer a distinct strategic advantage for recent graduates. The specific competencies required here, such as navigating novel protocols without historical documentation, managing irreversible operational risk, and auditing smart contracts, are areas where human judgment remains irreplaceable. An LLM can generate a standard back-testing script for the S&P 500 based on decades of public code, but it cannot effectively architect a risk engine for a brand-new Layer-2 blockchain protocol where the failure modes are not yet documented in any training set. Therefore, the "crypto premium" in the labor market is shifting from paying for speculation to paying for the ability to manage complexity and novelty in a high-stakes environment.

Pros and Cons of the Coinbase Ecosystem

The comparative advantage of beginning a quantitative career at Coinbase lies in the concept of "High Agency." Unlike traditional banks where quantitative roles often involve maintaining legacy models developed decades ago, Coinbase employees operate on the frontier of financial infrastructure. This provides an innovative environment where a junior engineer or data scientist can handle significant product verticals, resulting in rapid skill acquisition and distinct resume differentiation. Additionally, the compensation structure, often heavily weighted in liquid equity (RSUs), aligns employee incentives with the growth of the broader digital asset sector. However, these benefits come with significant costs. The 24/7 nature of the crypto markets creates a relentless operational tempo that distinguishes it from the structured work-life balance of traditional banking. The knowledge that a deployment error can result in irreversible loss of funds creates a high-pressure environment that is not suitable for all temperaments.

Strategic Preparation and Final Recommendations

For Duke students across Data Science, Computer Science, and Mathematics, the optimal strategy to navigate this competitive, AI-impacted job market is to develop interdisciplinary competency. It is no longer sufficient to be a pure data scientist who cleans CSV files, nor a pure developer who writes isolated code. The most valuable candidates are those who understand the plumbing of the asset class. Preparation should move beyond standard Kaggle datasets to include practical interaction with the technology. Employers like Coinbase need to see novel thinking even in simple projects, and they need to see a broad understanding of real-world complexity. By demonstrating the ability to navigate the messy, undocumented intersection of finance, software, statistics, and cryptography, students prove they possess the critical thinking and risk-management skills that AI cannot currently replicate, securing their leverage in a rapidly evolving digital economy. As ever, goal setting and planning remain vital to proper preparation, however, Duke University grants students the ability to diversify their skills across departments and develop foundational skills to become competitive job candidates.

References

[1] 1Token. Crypto funds 101: Funding fee arbitrage strategy, November 2024. Accessed:

2025.

[2] Damien Ackerer, Julien Hugonnier, and Urban Jermann. Perpetual futures pricing. Working Paper 32936, National Bureau of Economic Research, September 2024.

[3] Guillermo Angeris, Tarun Chitra, Alex Evans, and Matthew Lorig. A primer on perpetuals, 2022.

[4] Binance. Important updates on funding rates of usd-m perpetual contracts, 2023. Capped funding rate of $\pm 3\%$ for contracts with $\leq$25x leverage.

[5] Binance. Introduction to binance futures funding rates, 2023. Interest rate fixed at 0.03% daily, premium clamp at $\pm 0.05\%$.

[6] Binance. Binance futures fee structure and fee calculations, 2025. VIP0 maker fee 0.02%, taker fee 0.05%.

[7] Binance. How to use bnb to pay for fees and earn 25% discount, 2025. Spot trading base fee 0.1%, 25% discount with BNB.

[8] Bitget. Funding rate arbitrage decoded: How to achieve stable annualized returns through spot and perpetual hedging, December 2024.

[9] Fischer Black and Myron Scholes. The pricing of options and corporate liabilities. *Journal of Political Economy*, 81(3):637–654, 1973.

[10] BlackRock iShares. Bitcoin volatility guide: Trends and insights for investors, 2025. Bitcoin annualized volatility approximately 54%.

[11] Coinbase Global, Inc. Careers at coinbase, 2025.

[12] Coinbase Global, Inc. Coinbase q4 2024 shareholder letter. SEC Filing, February 2025.

[13] CoinGlass. Funding rates and arbitrage data, 2025. Real-time funding rate data.

[14] David Easley, Maureen O'Hara, Songshan Yang, and Zhibai Zhang. Microstructure and market dynamics in crypto markets, 2024.

[15] Gate.io. Perpetual contract funding rate arbitrage strategy in 2025, May 2025. Accessed: 2025.

[16] Songrun He, Asaf Manela, Omri Ross, and Victor von Wachter. Fundamentals of perpetual futures, 2024.

[17] Bernt Øksendal. *Stochastic Differential Equations: An Introduction with Applications*. Springer, 6th edition, 2003.

[18] Robert J. Shiller. Measuring asset values for cash settlement in derivative markets: Hedonic repeated measures indices and perpetual futures. *National Bureau of Economic Research Working Paper No. t0131*, 1993.

[19] S&P Global Market Intelligence. Coinbase's revenue mix increasingly driven by subscriptions, November 2025.

[20] George E. Uhlenbeck and Leonard S. Ornstein. On the theory of the brownian motion. *Physical Review*, 36(5):823–841, 1930.

[21] Oldrich Vasicek. An equilibrium characterization of the term structure. *Journal of Financial Economics*, 5(2):177–188, 1977.

[22] Warodom Werapun, Tanakorn Karode, Jakapan Suaboot, Tanwa Arpornthip, and Esther Sangiamkul. Exploring risk and return profiles of funding rate arbitrage on cex and dex. *Blockchain: Research and Applications*, page 100354, 2025.