# Return Predictability: Lessons and Insights for Future Hedge Fund Managers

## Crash Course - UASM

## August 2025

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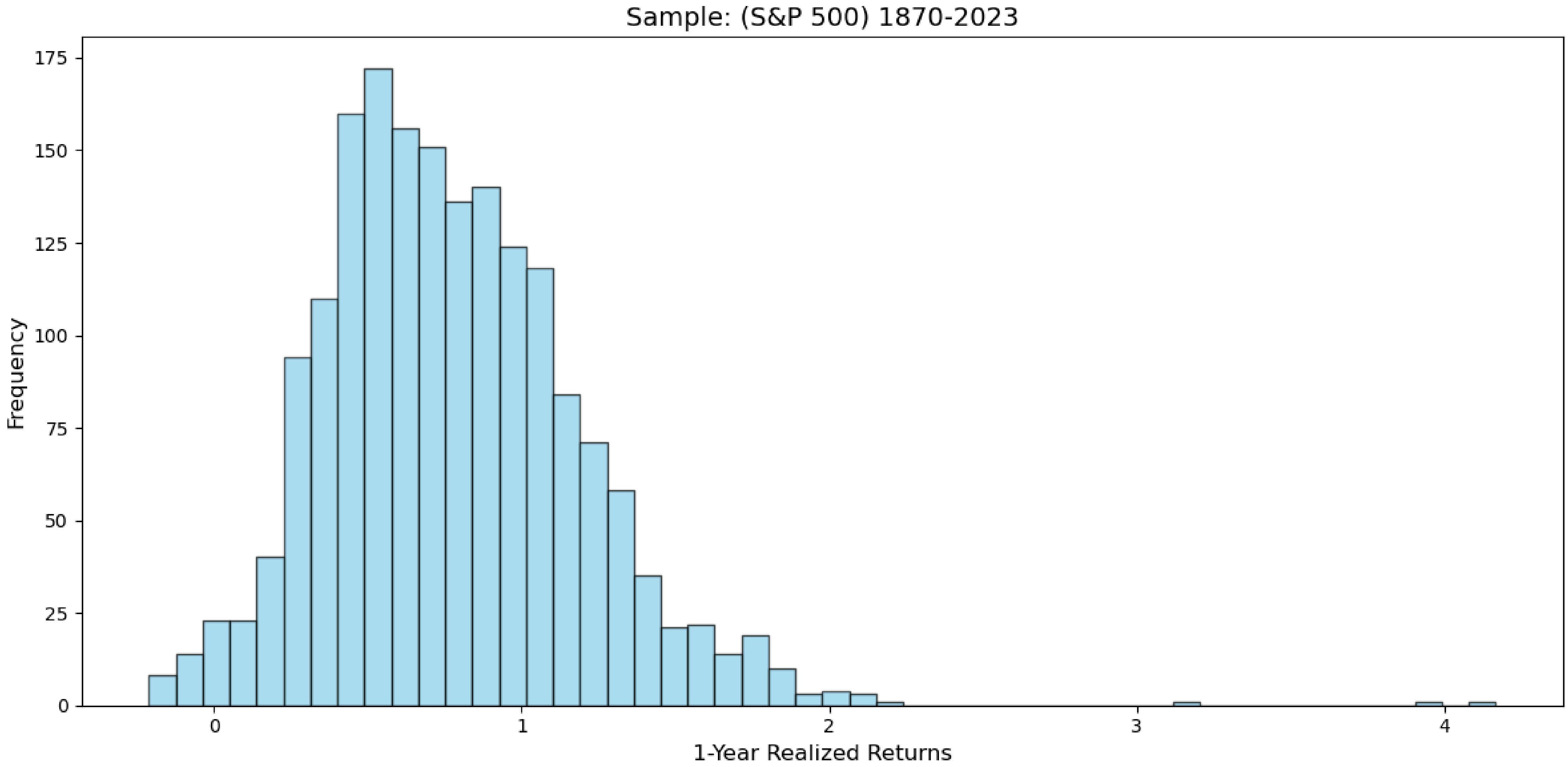
## Motivation

If you pick a month at random between 1870 and 2025, how does the compound realized return of the SP500 **one year ahead** look like?



Sample: (S&P 500) 1870-2023
Frequency
175
150
125
100
75
50
25
0
0
1
2
3
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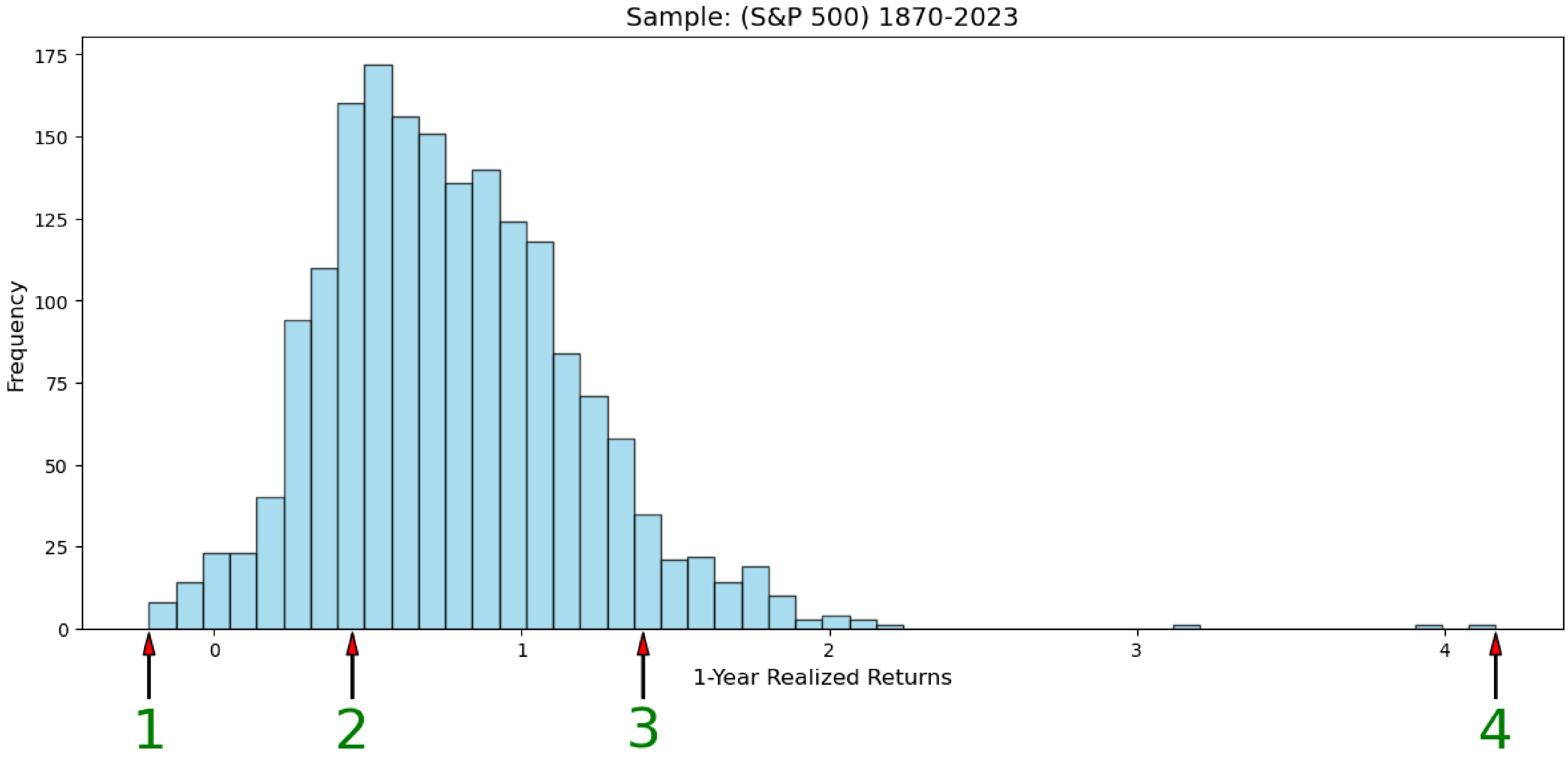
1-Year Realized Returns



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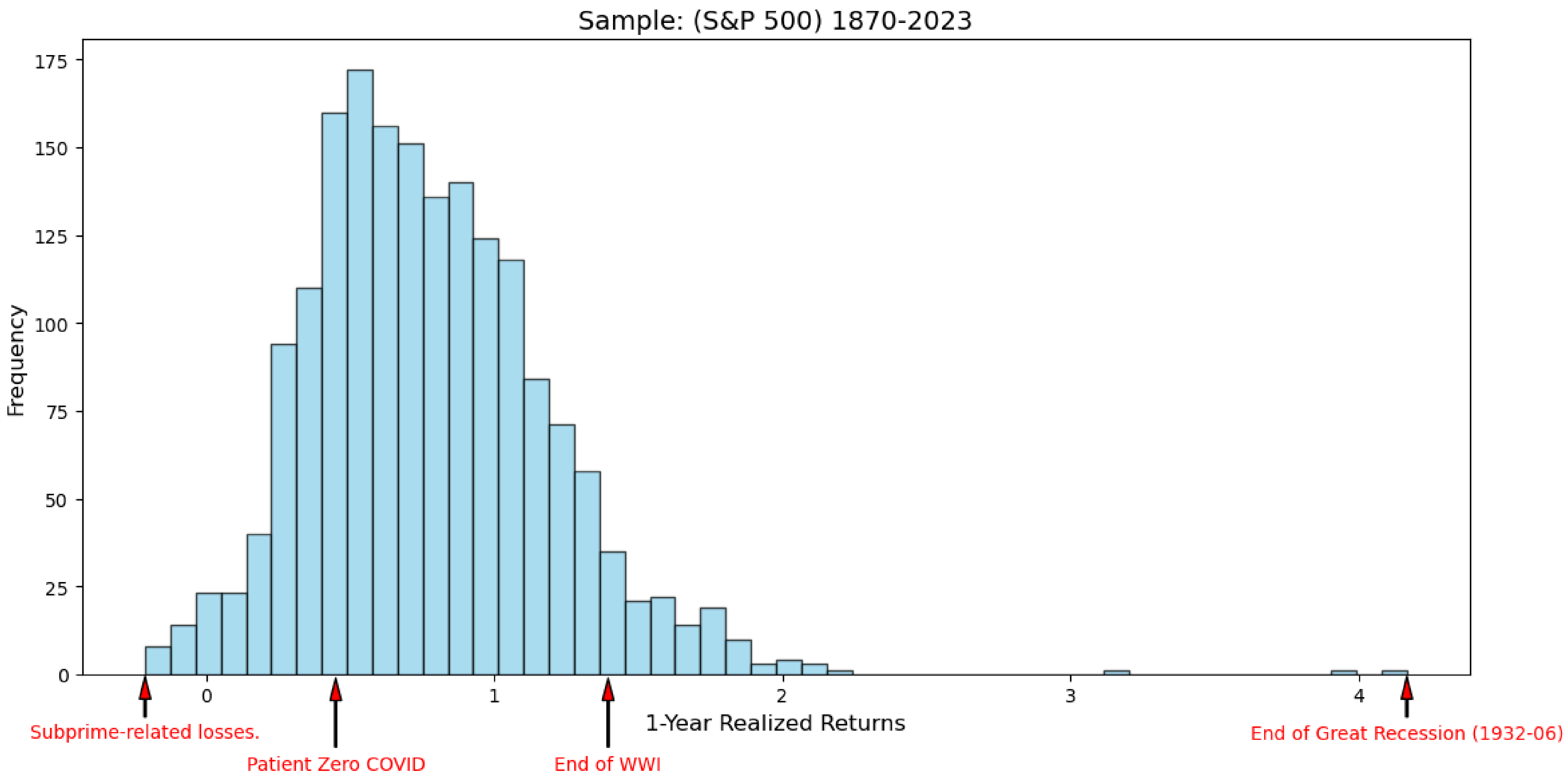
## Guessing the events

- End of Great Recession (1932-06)
- Patient Zero COVID (2019-12)
- Banks Recognise Subprime-related losses (2007-12)
- End of WW1 (1918-11)



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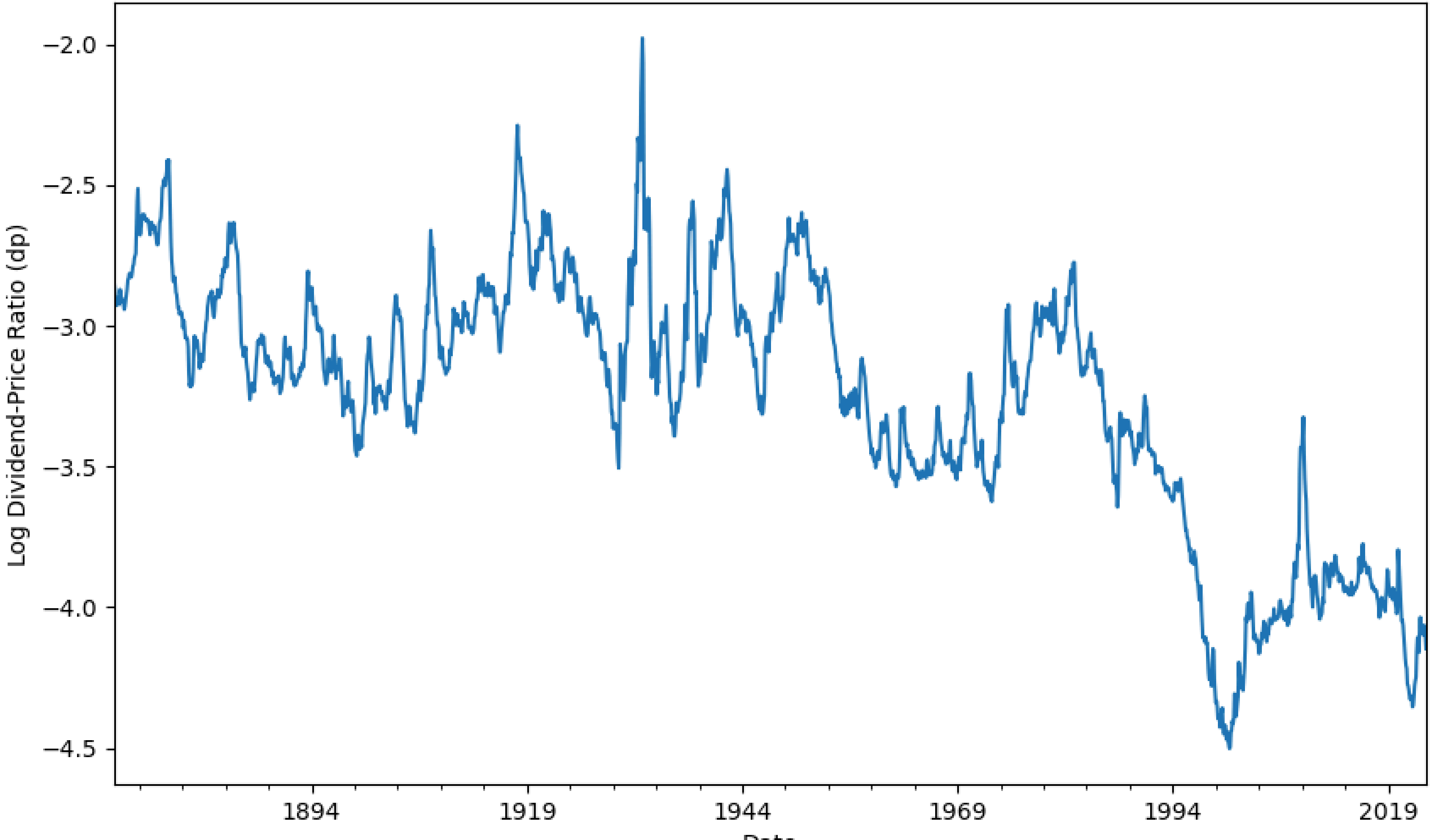
Subprime-related losses.
Patient Zero COVID
End of WWI
End of Great Recession (1932-06)

## Business Cycles

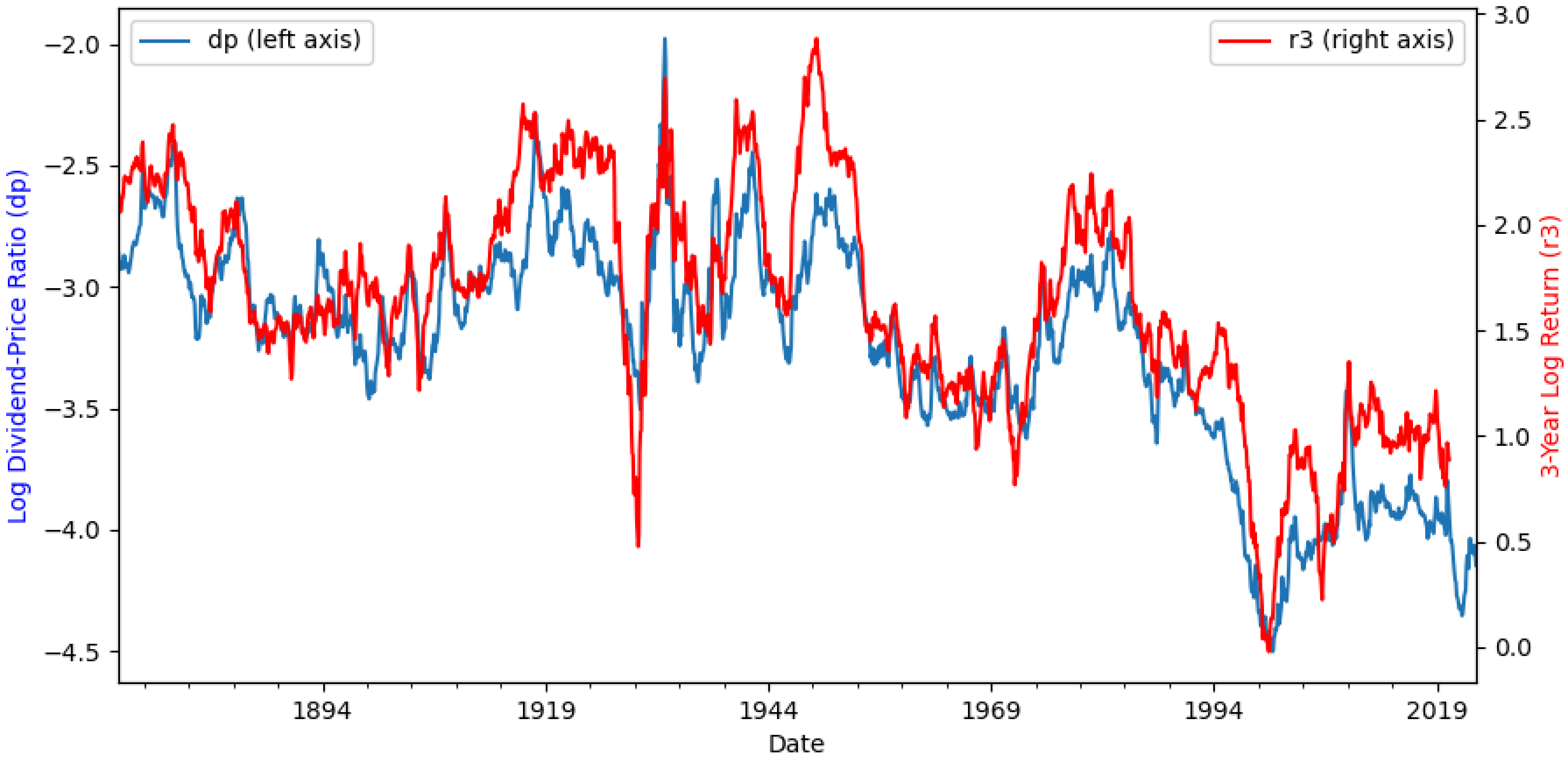
What do periods of low/high expected returns have in common?

- Assets seem to be **cheap** when expected returns are high.
- Assets seem to be **expensive** when expected returns are low.
- A ratio of how much an asset is paying (e.g. dividends) vs its price is a good indicator of where in the business cycle we are.
- This applies to all assets, not just stocks, e.g. how much rent you can get from a house vs its price.

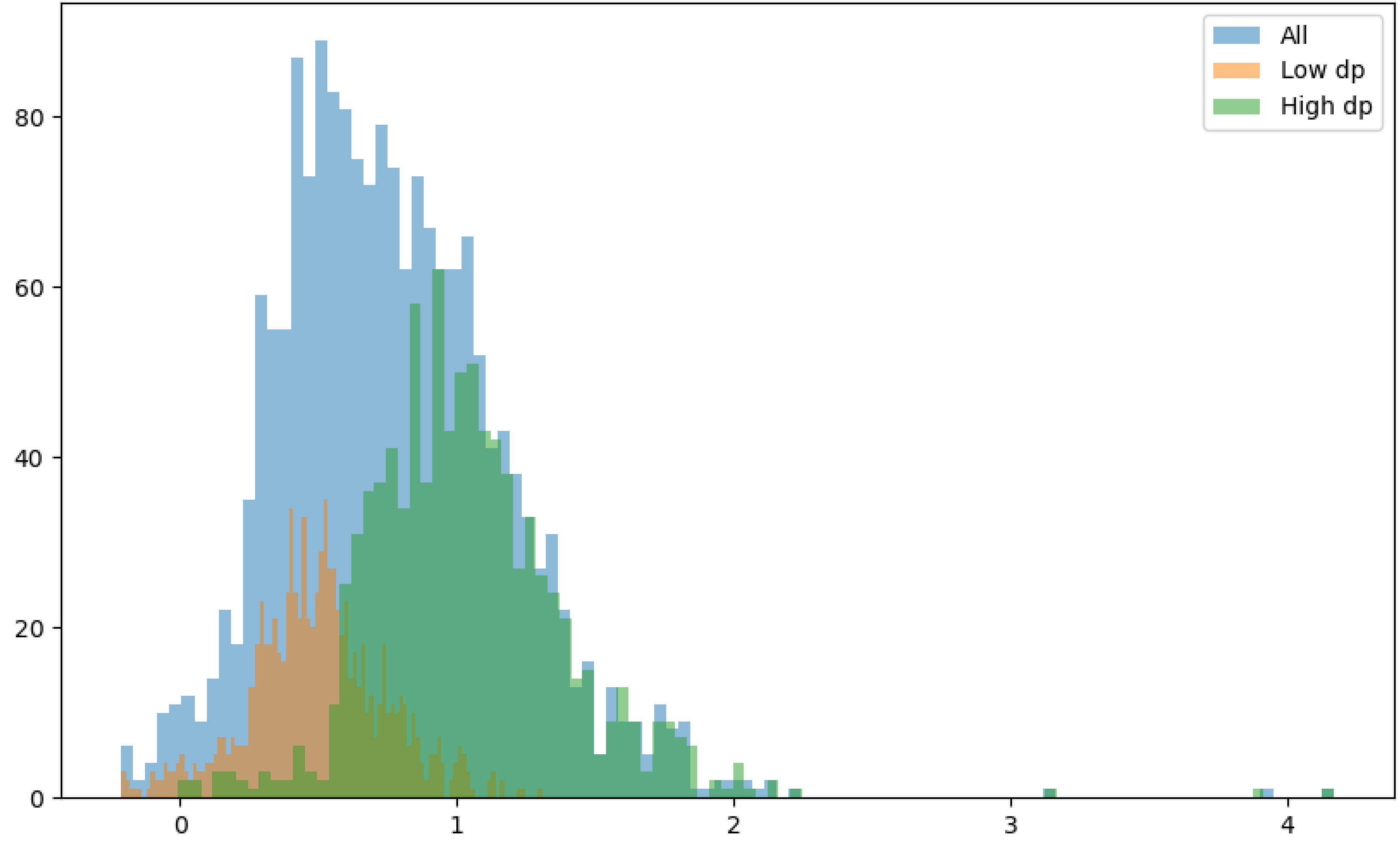
# D/P variation over time



# D/P and 3-year ahead returns



# How does the D/P capture return variation?



# Market Efficiency: Overview and Evidence

- **Animal Spirits** (Keynes, 1936): Prices are driven by irrational behavior and sentiment.
- **Efficient Market Hypothesis** (Fama 1970, Malkiel 1973): Prices in Financial Markets reflect all available information, and returns are unpredictable.
- **Behavioral Finance** (Shiller, 1981): Prices are driven by irrational behavior and sentiment.
- Debate between how ***should*** markets behave (normative) vs how ***do*** markets behave (positive).

## Modern Approach

- **Efficient Inefficiently** (Pedersen, 2019): The idea that markets are efficient enough to reflect relevant information into prices but inefficient enough to incentivize market participants to gather information and trade.
- Markets do react to new information, but the reaction is not always immediate nor rational.
- If markets were not efficient enough then it would be **easy** to make money.
- It markets were not inefficient, how do we justify hedge fund fees structure of 2/20? 2% of assets and 20% of profits.

## What do we mean for predictability?

- **Intuition**: Can we find a variable that helps be right on average on the direction and magnitude of future returns?

- **Formal definition**, conditional vs unconditional expectations.

$$\mathbb{E}[R_{t\to t+\tau}|X_t] \neq \mathbb{E}[R_{t\to t+\tau}]$$

## How do we search for predictability?

- **Data**: Data collection vs Data Exhaustion. $\rightarrow$ Market Efficiency.
- **Economic Theory**: What variables should be relevant?
- **Model**: Linear vs Non-Linear $\rightarrow$ Economic Mechanisms vs Spurious Correlations.
- **Backtesting**: Implementation and Transaction Costs.
- **Risk Management**: How to manage the risk of a strategy that is not always profitable?

## Time-Series and Cross-sectional Predictability

- **Time-Series**: Can you time the market? Can you time an industry? Can you buy low and sell high?
- **Cross-sectional**: Can you pick the best stocks? Can you pick the best industries? Why do some stocks outperform others?

## Why is it predictability important for Hedge Funds?

- Mandate on generating returns **regardless of market conditions**.
- Flows are extremely sensitive to performance.
- Huge fees, deregulation, and access to financial technology and leverage means that the competition is fierce and expectations are high.
- Access to technology, traders, and real time information: **timing the market**.
- Access to a large universe of assets: **cross-sectional predictability**.

## Simplest Tool, Linear Regression

Find Signal $X_t$ such that

$$R_{t \to t+\tau} = a + \beta X_t + \epsilon_{t \to t+\tau}$$

- $\hat{\beta} \neq 0$: Predictability, $\mathbb{E}[R_{t \to t+\tau}] = \hat{a} + \hat{\beta} X_t$
- But what if its just luck? $\to$ **Significance Testing**.
- Look at standard errors.

## Out-of-Sample Predictability / Backtesting.

- Even if $\hat{\beta} \neq 0$, it does not mean that we can make money.
- **Out-of-Sample**: Test the strategy on a different sample.
- It normally requires a **rolling** estimation of the model.

## Long-term Experiment

Consider two timing strategies on the SP500, no leverage constraints.

- Buy/short the market if the rolling expected return over the next 3 years is positive/negative.
- Buy/short the market if the rolling expected return predicted by the log dividend price ratio is positive/negative.
- Rule of Thumb of Sharpe Ratios of 3.

## Entire Sample: 1871-2023

| Strategy | Average Return | Annual Volatility | Approx. Sharpe Ratio | Overall |
|---|---|---|---|---|
| Benchmark | 0.45 | 0.17 | 2.63 | ⚠️ |
| Linear Model | 0.54 | 0.15 | 3.67 | ✅ |

## Post-war Sample: 1946-2023

| Strategy | Average Return | Annual Volatility | Approx. Sharpe Ratio | Overall |
|---|---|---|---|---|
| Benchmark | 0.26 | 0.17 | 1.56 | 🚨 |
| Linear Model | 0.42 | 0.13 | 3.28 | ✅ |

## 1970-2023

| Strategy | Average Return | Annual Volatility | Approx. Sharpe Ratio | Overall |
|---|---|---|---|---|
| Benchmark | 0.22 | 0.16 | 1.35 | 🚨 |
| Linear Model | 0.39 | 0.13 | 2.93 | ✅ |

## 1990-2023

| Strategy | Average Return | Annual Volatility | Approx. Sharpe Ratio | Overall |
|---|---|---|---|---|
| Benchmark | 0.06 | 0.16 | 0.38 | 🚨 |
| Linear Model | 0.26 | 0.14 | 1.95 | ⚠️ |

## Predictability works better across shorter samples

- Expected returns over longer samples capture macroeconomic trends, risk premia, consumption growth, productivity growth, etc.
- Regardless of the source of predictability (risk vs mispricing), its profits tend to diminish over time.
- This is due to the statistical behavior of what we are trying to predict.
- My favorite analogy: **General Relativity vs Quantum Mechanics**, over long distances/extended periods of time you just follow the laws of physics, but at the micro-level, things get weird.

## More complex relationships

- **Non-linearities**: Many signals, that are not linearly related to returns.

$$R_{t\to t+\tau} = f(X_{1t}, X_{2t}, \ldots, X_{kt}) + \epsilon_{t\to t+\tau}$$

- **Machine Learning**: Can we use more complex models to predict returns?
- **Pros**: Strategies can be more profitable as it can capture more complex relationships.
- **Cons**: Overfitting, Black-box, and lack of economic intuition.
- **Alternative Data**:
    - Satellite images,
    - Social Media,
    - Credit Card Transactions,
    - Walking patterns

## Does ML work?

It does if you are careful.

- Evidence across equity markets exploiting **publicly available data**, it is not about gathering additional data but learning from it (Kelly et al. 2020).
- **Retail Investors could benefit from ML**: Publicly available data and ML can help select Mutual Funds with positive alpha (DeMiguel et al. 2023).
- Allows for **in-house** development of strategies that are not available to the general public.

## Artificial Intelligence and Natural Language Processing

- So far we have assumed $X_t$ is a number.
- 2023 Q4 Apple Inc's 10-K report contains only 6.91% of numerical characters.
- **Natural Language Processing**: Can we extract information from text?
  - Companies' reports,
  - Central Bank Statements,
  - News Articles,
  - Earnings Calls.
  - Social Media.

## Why Text Matters in Investing

- Much of the information in finance is conveyed through words, not just numbers.
- Words can reveal emotions, intentions, and subtle cues that quantitative data misses.
- Intuition: Like reading between the lines in a business meeting.

## Sentiment Analysis Basics

- **Sentiment**: The emotional tone behind words – positive, negative, or neutral.
- Algorithms analyze text to score sentiment, similar to how humans judge a conversation.
- Business intuition: A positive tone in a CEO's speech might predict better company performance.

## Text-Based Signals in Practice

- **Earnings Calls**: The tone of executives can predict stock price movements.
- **News Articles**: Negative coverage often leads to immediate market drops.
- **Social Media**: Public sentiment on platforms like Twitter influences retail trading.

## Challenges with Text Data

- Text can be ambiguous: sarcasm, irony, or context-dependent meanings.
- Not all information is useful; some is just noise.
- Over-relying on text without combining with numbers can lead to poor decisions.

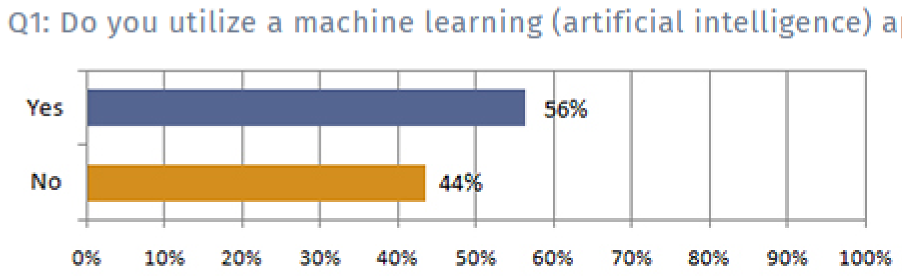
## Integrating Text into Investment Strategies

- Combine text signals with traditional financial metrics for better predictions.
- Hedge funds use NLP to gain an edge in timing trades or selecting stocks.
- Intuition: It's like having a translator for the "human" side of markets.

# AI Adoption

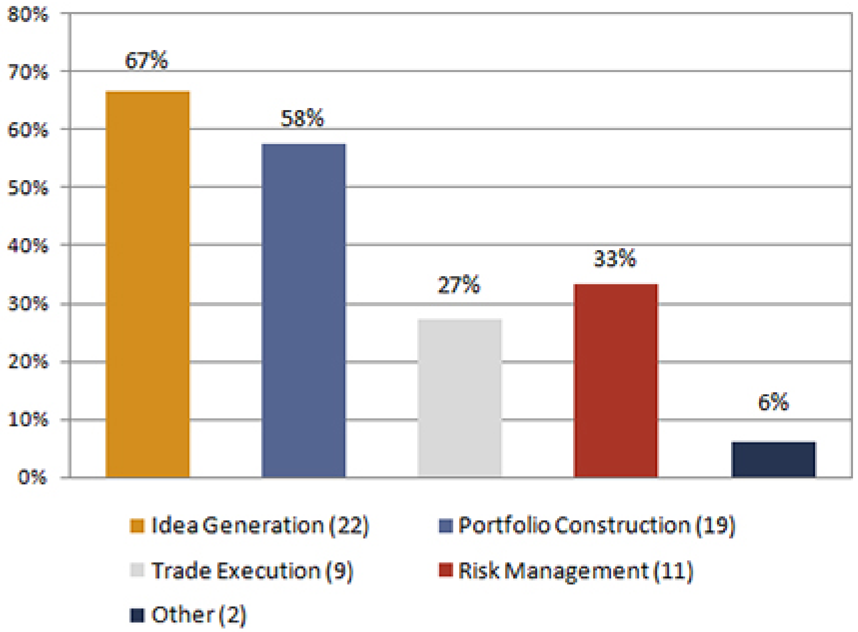
A BarclayHedge survey of 55 hedge fund/CTA professionals

- Q1: Do you utilize a machine learning (artificial intelligence) approach in your investment processes?



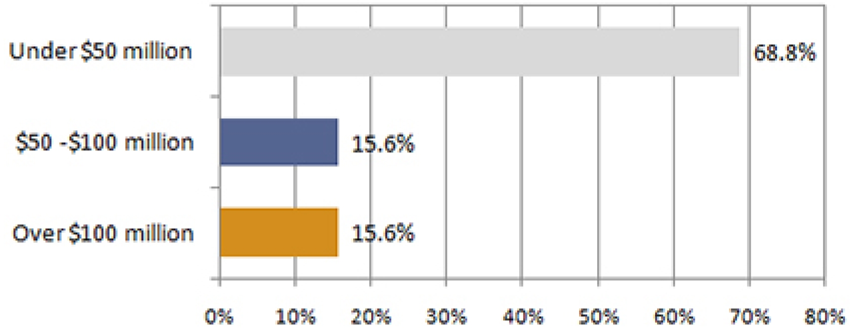
# AI Adoption

- Q2: Which part of your investment process is driven by an application of machine learning techniques?



# AI Adoption

- Q5: What are your approximate total strategy assets that utilize machine learning/artificial intelligence (funds and managed accounts)?



# Conclusions

- **Return predictability exists** and varies systematically with business cycles and market conditions
- **Modern hedge funds** increasingly leverage AI, NLP, and alternative data sources to gain competitive advantages
- **Success requires** combining traditional financial metrics with innovative approaches and rigorous risk management

# Questions?

Thank you for your attention!