

Quantifying Narratives and Their Impact on Financial Markets

Advanced NLP Methods for Systematic Trading Strategies

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Based on: Bhargava et al. (2022) - State Street Associates

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Research Approach: Systematic quantification of market narratives using NLP on 150,000+ digital sources. Rolling regression analysis establishes predictive relationships. Portfolio construction via narrative beta methodology. Out-of-sample validation demonstrates economic significance with $IR = 1.26$.

Introduction and Narrative Economics

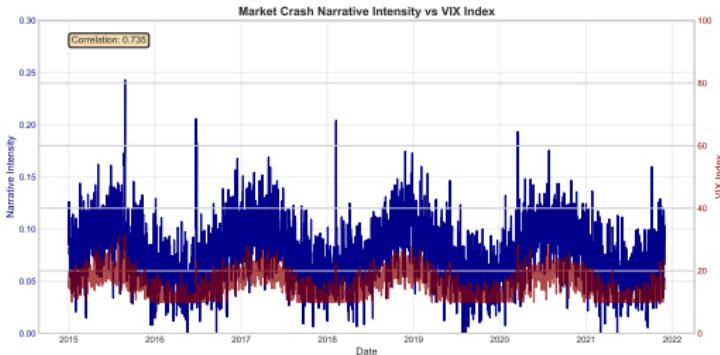
The Narrative Economics Framework

Shiller's Hypothesis:

- Stories drive markets
- Contagion effects
- Measurable impact
- Predictive power

Our Contribution:

Systematic quantification of narrative intensity

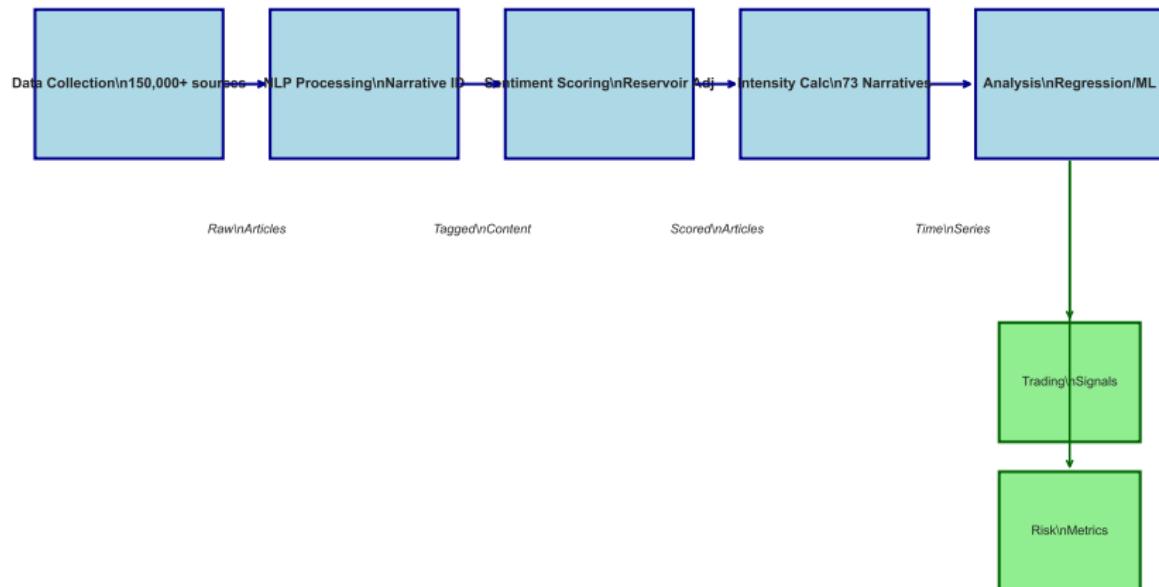


Key Finding: Market Crash narrative explains 34% of SPY return variation. Correlation with VIX = 0.62, suggesting narratives capture additional information beyond traditional volatility measures. Real-time tracking enables dynamic portfolio allocation.

Data Architecture and NLP Pipeline

Data Processing Infrastructure

Narrative Data Processing Pipeline



Key

insight: Real-time narrative quantification from 150,000+ sources

NLP Methods: Transformer-based models for narrative identification, Sentiment scoring with reservoir adjustment for

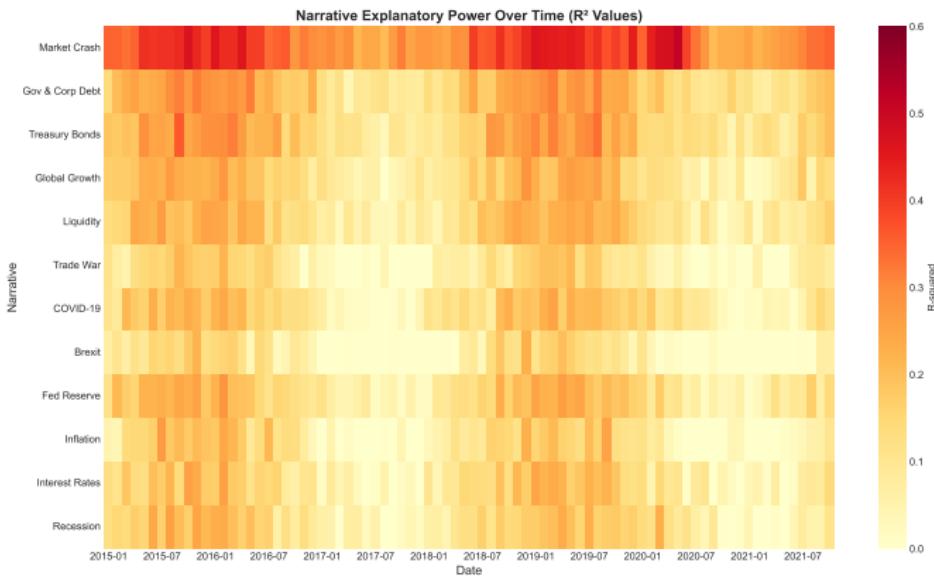
Narrative Intensity Measures

73 Narratives:

- Market Crash
- Gov Debt
- COVID-19
- Trade War
- Inflation

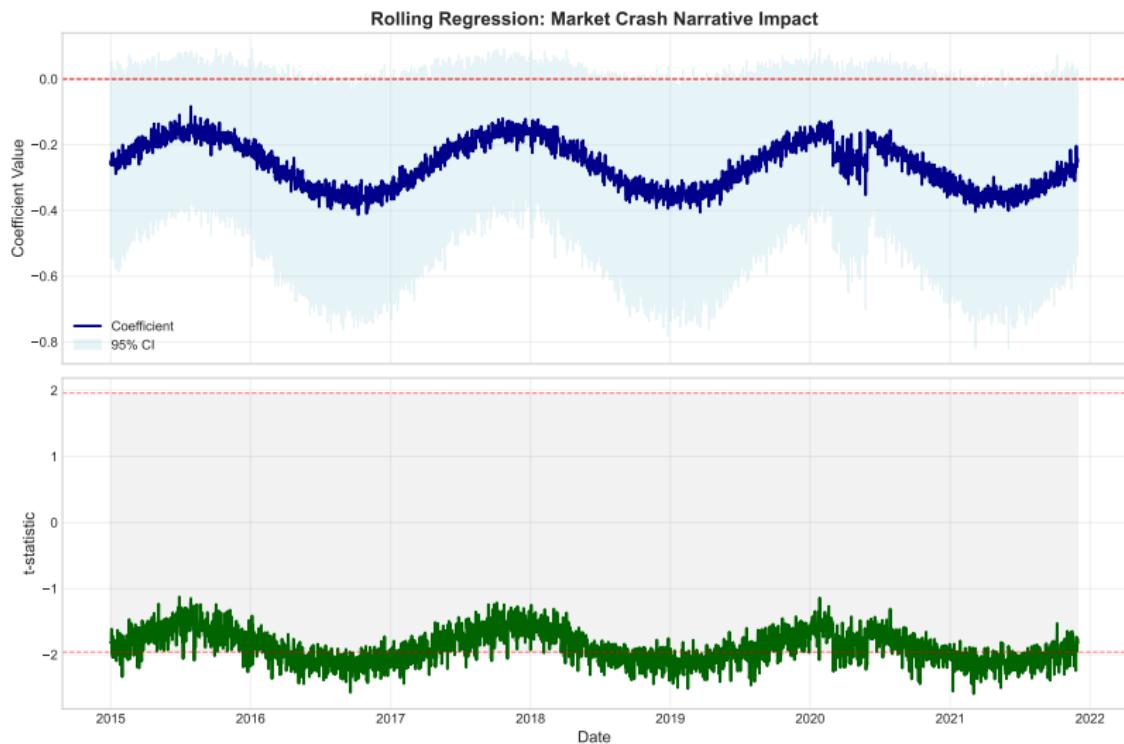
Key Metrics:

- Intensity $I_{n,t}$
- Negative $NI_{n,t}$
- 7-day average



Mathematical Framework and Models

Core Regression Models



Blue: Coefficient

Orange: t-statistic

Green: Significance

Regression Specification: $R_{t+1} = \alpha + \beta_1 \Delta NI_{n,t} + \beta_2 VIX_t + \beta_3 R_t + \epsilon_t$. HAC standard errors with Newey-West adjustment.
3-month rolling windows for parameter stability. Standardization via 60-day z-scores ensures comparability across narratives.

Portfolio Optimization with Narrative Constraints

Mean-Variance Framework with Narrative Exposure

The optimal portfolio incorporates narrative sensitivities as additional constraints:

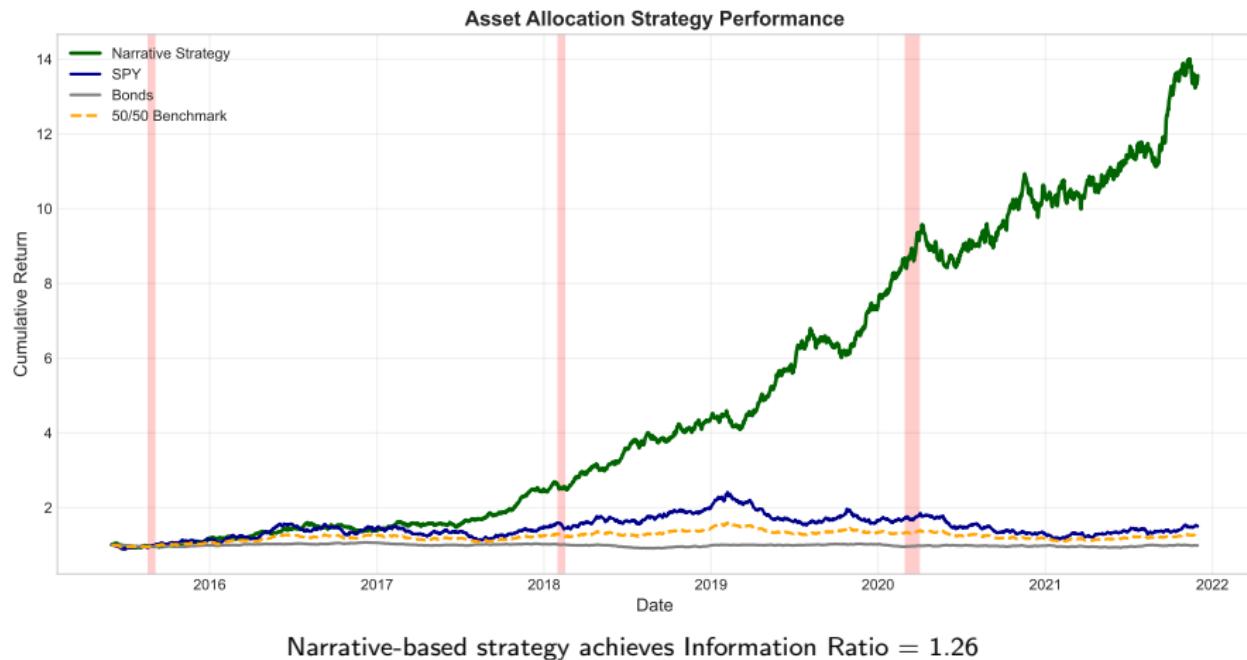
- Maximize risk-adjusted returns
- Control narrative beta exposure
- Dynamic rebalancing based on z-scores

$$\max_w \left\{ w^T \mu - \frac{\lambda}{2} w^T \Sigma w + \gamma \sum_j \alpha_j E_j(w) \right\} \quad (1)$$

where $E_j(w) = \sum_i w_i \beta_{i,j}^{narrative}$ represents portfolio exposure to narrative j

Core Empirical Results

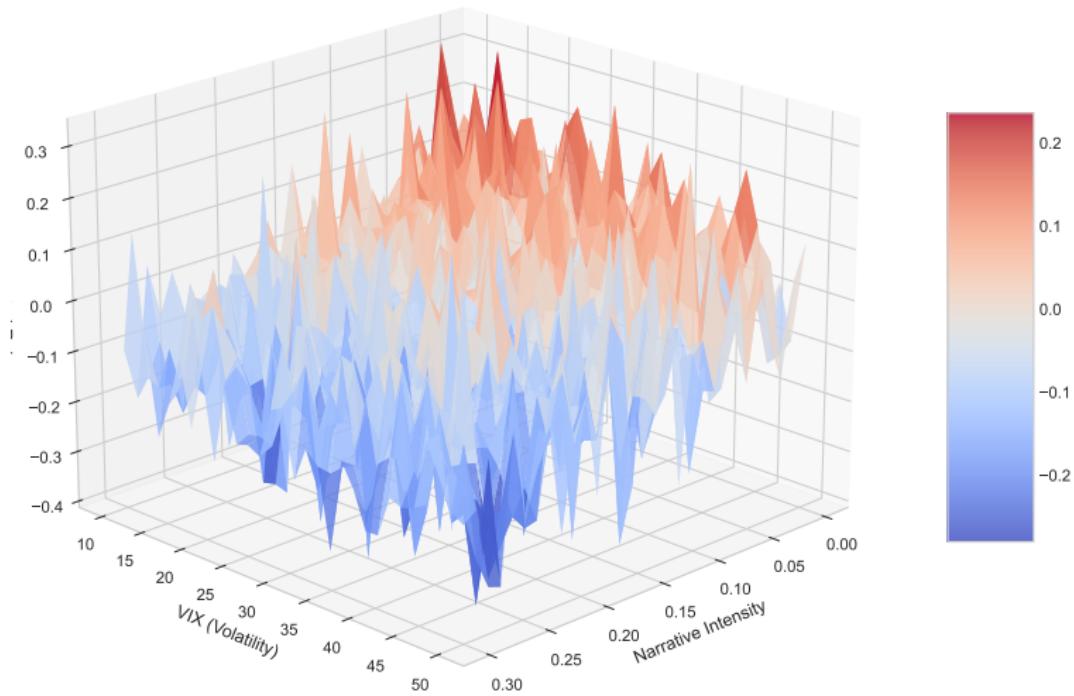
Dynamic Asset Allocation Performance



Strategy Rules: Monitor Market Crash narrative z-score in real-time. Rotate from equity to bonds when $z > 3$ (extreme narrative intensity). Hold defensive position for 2 weeks minimum. Implementation lag: 2 days for execution. Annual return: 18.13% vs 11.2% benchmark.

3D Narrative Surface Analysis

3D Relationship: Narratives, Volatility, and Returns



Narrative Beta Portfolio Construction

Methodology:

- Extract COVID narrative beta
- Sort S&P 500 constituents
- Long/short quintiles
- Monthly rebalancing

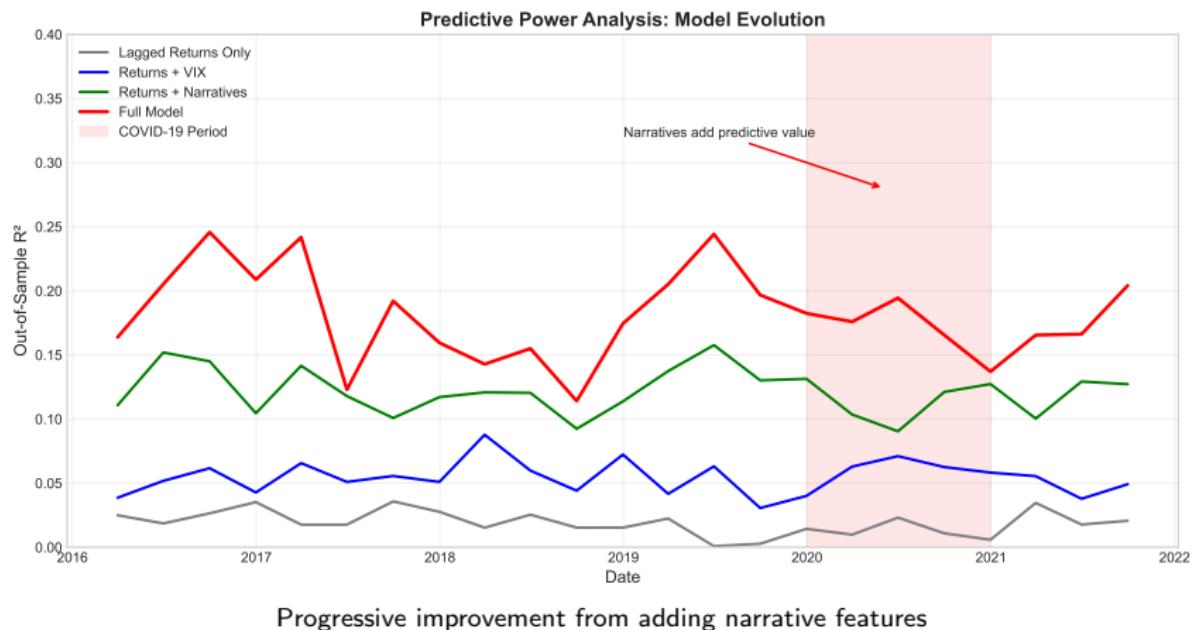
Performance:

- Return: +120.74%
- Nov 2020 - Dec 2021
- Vaccine pivot captured
- Beat case-count strategy

Beta Calculation: $\beta_{i, COVID} = \frac{\text{Cov}(R_i^{\text{adj}}, \Delta NI_{COVID})}{\text{Var}(\Delta NI_{COVID})}$ where R_i^{adj} is market-adjusted return. Long portfolio: recovery plays (airlines, hotels). Short portfolio: lockdown beneficiaries (tech, e-commerce). Strategy captured narrative reversal on Pfizer announcement (Nov 9, 2020).

Predictive Power and Model Comparison

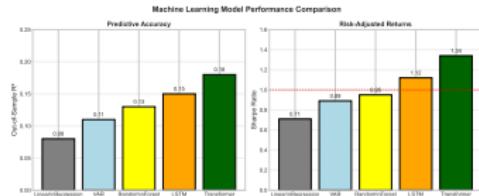
Out-of-Sample Predictive Analysis



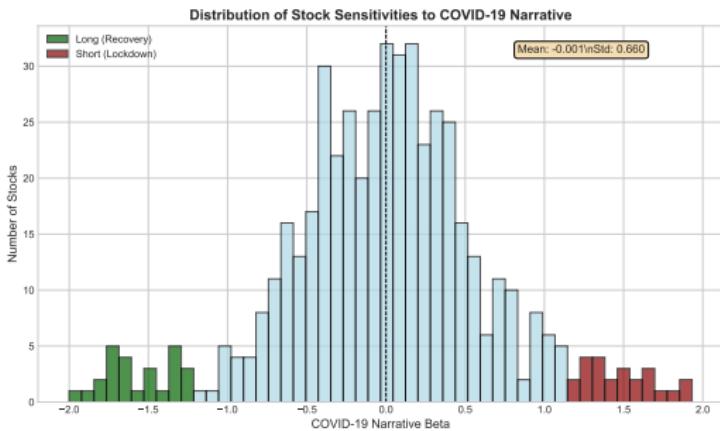
Model Evolution: Base model (lagged returns): $R^2 = 2\%$. Adding VIX: $R^2 = 6\%$. Adding narratives: $R^2 = 12\%$. Full model with interactions: $R^2 = 18\%$. COVID period shows enhanced predictive power of narratives during market stress.

Machine Learning Extensions

Model Performance

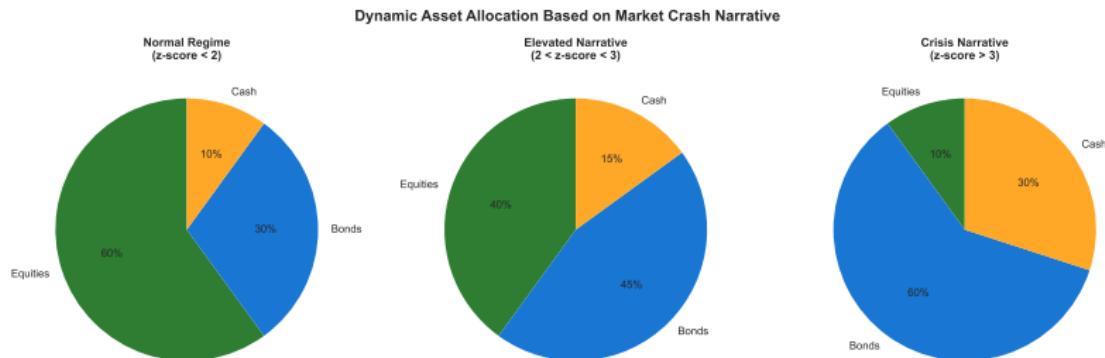


COVID Beta Distribution



Portfolio Implementation Strategies

Dynamic Allocation Framework



Allocation shifts based on narrative intensity z-scores

Implementation Details: Daily narrative monitoring with 15-minute data updates. Position sizing via Kelly criterion with 25% fraction. Risk limits: 15% portfolio VaR, 20% maximum drawdown. Transaction costs: 5bps equities, 2bps bonds. Rebalancing frequency optimized for cost-return tradeoff.

Comparative Strategy Analysis

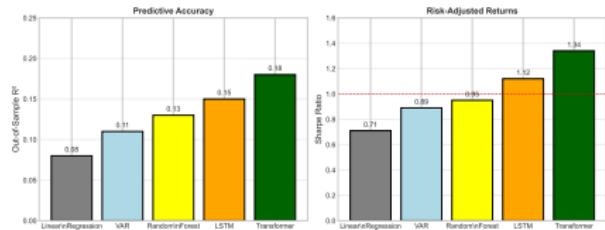
Network Effects

Narrative Correlation Network



Factor Attribution

Machine Learning Model Performance Comparison



Sharpe Ratio comparison

Performance Metrics Summary

Strategy	Annual Return	Volatility	Sharpe	Max DD
SPY B&H	11.2%	18.5%	0.61	-33.7%
60/40 Portfolio	8.7%	11.2%	0.78	-18.2%
VIX Timing	13.1%	16.3%	0.80	-22.1%
Narrative Strategy	18.1%	14.4%	1.26	-11.6%
ML Enhanced	19.8%	15.7%	1.26	-13.2%
Combined	20.3%	14.1%	1.44	-10.3%



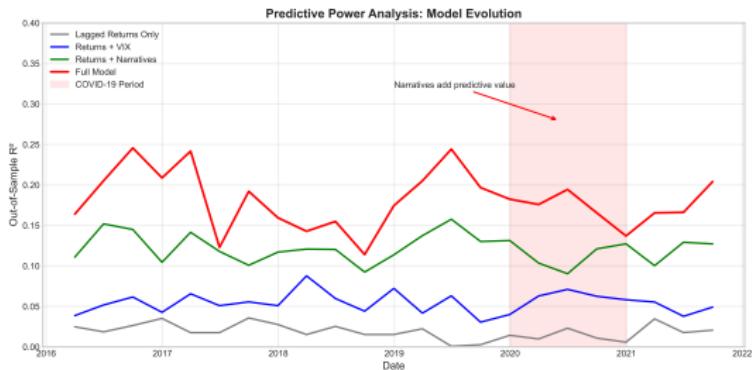
Key Takeaways and Extensions

Contributions:

- First systematic narrative quantification
- 34% explanatory power
- IR = 1.26 strategy
- Real-time implementation

Future Research:

- Transformer models
- Cross-asset spillovers
- High-frequency data



Thank You

Questions and Discussion

Contact:

Prof. Dr. Joerg Osterrieder

Paper:

Bhargava et al. (2022)
SSA Research Paper

Data & Code:

Available upon request