Mathematical Theory of Narrative Economics

Stochastic Models and Econometric Methods for Narrative Quantification

Prof. Dr. Joerg Osterrieder

Advanced Mathematical Finance Seminar

September 19, 2025

Theoretical Framework Overview

Focus: Mathematical foundations and theoretical models for narrative dynamics in financial markets. Emphasis on rigorous econometric identification, stochastic process theory, and optimal control. Empirical validation relegated to appendix.

Mathematical Foundations of Narrative Economics

SIR-Type Dynamics for Narrative Spread

Let $S(t)$, $I(t)$, $R(t)$ denote susceptible, infected, and recovered populations:

$$\frac{dI}{dt} = \beta S(t)I(t) - \gamma I(t) + \eta(t) \tag{1}$$

$$\frac{dS}{dt} = -\beta S(t)I(t) + \delta R(t) \tag{2}$$

$$\frac{dR}{dt} = \gamma I(t) - \delta R(t) \tag{3}$$

where $\eta(t)$ represents exogenous narrative shocks (news events).

Basic Reproduction Number: $R_0 = \frac{\beta}{\gamma}$

Critical Threshold: Narrative becomes viral when $R_0 > 1$

Extension: Multi-narrative competition via coupled SIR systems with cross-immunity terms.

Shannon Entropy and Mutual Information
Narrative uncertainty measured via entropy:

$$H(N) = -\sum_{n \in \mathcal{N}} p(n) \log_2 p(n) \tag{4}$$

Information content about returns:

$$I(N;R) = \sum_{n,r} p(n,r) \log_2 \frac{p(n,r)}{p(n)p(r)} = H(R) - H(R|N) \tag{5}$$

Transfer Entropy (directional causality):

$$TE_{N \to R} = \sum p(r_{t+1}, r_t^k, n_t^l) \log \frac{p(r_{t+1}|r_t^k, n_t^l)}{p(r_{t+1}|r_t^k)} \tag{6}$$

Theorem: $TE_{N \to R} > 0$ implies Granger causality from narratives to returns.

Stochastic Process Models

Jump-Diffusion Narrative Intensity

Narrative intensity N_t follows:

$$dN_t = \kappa(\theta - N_t)dt + \sigma\sqrt{N_t}dW_t + hdJ_t \tag{7}$$

where:

- κ: mean reversion speed
- θ: long-run mean intensity
- σ: diffusion volatility
- J_t: Poisson process with intensity λ
- h: jump size (drawn from $\mathcal{N}(\mu_J, \sigma_J^2)$)

Moment Generating Function:

$$\mathbb{E}[e^{uN_T}] = \exp\left\{A(T-t,u) + B(T-t,u)N_t\right\} \tag{8}$$

where $A(\cdot)$ and $B(\cdot)$ solve Riccati ODEs.

Self-Exciting Point Process Model
Intensity of narrative events:

$$\lambda(t) = \mu + \sum_{t_i < t} \phi(t - t_i) \tag{9}$$

Exponential kernel: $\phi(t) = \alpha e^{-\beta t}$
Branching ratio: $n = \frac{\alpha}{\beta} < 1$ (stability condition)
Proposition: The expected number of events triggered by a single event:

$$\mathbb{E}[\text{offspring}] = \int_0^\infty \phi(s) ds = \frac{\alpha}{\beta} \tag{10}$$

Application: Model clustering of narrative events (e.g., cascade of negative news).

Bond Percolation on Narrative Networks
Consider narrative spread on network $G(V, E)$ with bond probability p:
Critical Threshold:

$$p_c = \frac{1}{\lambda_{\max}(A) - 1} \tag{11}$$

where $\lambda_{\max}(A)$ is the largest eigenvalue of adjacency matrix.
Giant Component Size: For $p > p_c$, fraction in giant component:

$$S = 1 - \exp(-S \cdot z \cdot p) \tag{12}$$

where z is average degree.
Phase Transition:

- $p < p_c$: Narrative remains localized (subcritical)
- $p = p_c$: Critical point (power-law cluster sizes)
- $p > p_c$: Global narrative contagion (supercritical)

Fisher Information and Divergence Measures

Fisher Information Matrix for Narrative Parameters
For parameter vector $\boldsymbol{\theta} = (\beta, \kappa, \sigma, \lambda)$:

$$\mathcal{I}(\boldsymbol{\theta})_{ij} = -\mathbb{E}\left[\frac{\partial^2 \log L(\boldsymbol{\theta}|N)}{\partial\theta_i \partial\theta_j}\right] \tag{13}$$

Cramér-Rao Bound:

$$\text{Var}(\hat{\theta}_i) \geq [\mathcal{I}^{-1}(\boldsymbol{\theta})]_{ii} \tag{14}$$

Divergence Measures Between Narrative Distributions:
KL Divergence:

$$D_{KL}(P||Q) = \int p(n) \log \frac{p(n)}{q(n)} dn \tag{15}$$

Wasserstein Distance:

$$W_p(P, Q) = \left(\inf_{\gamma \in \Pi(P,Q)} \int ||x - y||^p d\gamma(x, y)\right)^{1/p} \tag{16}$$

Advanced Econometric Theory

High-Dimensional Narrative Selection

LASSO with Time-Varying Penalties
Objective function for narrative selection:

$$\hat{\beta} = \arg\min_{\beta} \frac{1}{T}\sum_{t=1}^{T}(r_t - \boldsymbol{n}_t'\beta)^2 + \sum_{j=1}^{p}\lambda_j(t)|\beta_j| \tag{17}$$

Adaptive weights: $\lambda_j(t) = \lambda \cdot \hat{\sigma}_j / |\hat{\beta}_j^{OLS}|^\gamma$
Oracle Property: Under conditions:

1. $\lambda_T/\sqrt{T} \to 0$ and $\lambda_T T^{(\gamma-1)/2} \to \infty$
2. Irrepresentable condition holds

Then: $P(\hat{\mathcal{S}} = \mathcal{S}^*) \to 1$ and $\sqrt{T}(\hat{\beta}_{\mathcal{S}^*} - \beta^*_{\mathcal{S}^*}) \xrightarrow{d} \mathcal{N}(0, \Sigma)$

Identification via Narrative Shocks

Instrumental Variables Approach
Structural equation:

$$r_t = \alpha + \beta n_t + \gamma' \boldsymbol{x}_t + \epsilon_t \tag{18}$$

where $\mathbb{E}[n_t \epsilon_t] \neq 0$ (endogeneity).
Instrument: Unexpected narrative shocks z_t from:

- Natural disasters mentioning specific narratives
- Predetermined media coverage cycles
- Regulatory announcements

2SLS Estimator:

$$\text{First stage:} \quad n_t = \pi_0 + \pi_1 z_t + \pi_2' \boldsymbol{x}_t + v_t \tag{19}$$

$$\text{Second stage:} \quad r_t = \alpha + \beta \hat{n}_t + \gamma' \boldsymbol{x}_t + u_t \tag{20}$$

Validity: $\mathbb{E}[z_t \epsilon_t] = 0$ and $\pi_1 \neq 0$ (relevance)

DiD for Narrative Policy Shocks
Treatment effect of narrative intervention:

$$Y_{it} = \alpha + \beta(Treat_i \times Post_t) + \gamma_i + \delta_t + \epsilon_{it} \tag{21}$$

Parallel Trends Assumption:

$$\mathbb{E}[Y_{i,t+1}^{(0)} - Y_{i,t}^{(0)} | Treat_i = 1] = \mathbb{E}[Y_{i,t+1}^{(0)} - Y_{i,t}^{(0)} | Treat_i = 0] \tag{22}$$

Synthetic Control Method:
Find weights $W^* = (w_1, ..., w_J)$ minimizing:

$$||X_1 - X_0 W||_V = \sqrt{(X_1 - X_0 W)' V (X_1 - X_0 W)} \tag{23}$$

Treatment effect: $\hat{\alpha}_{1t} = Y_{1t} - \sum_{j=2}^{J+1} w_j^* Y_{jt}$
Application: Evaluate impact of central bank narrative shifts on markets.

Factor Models for Narrative Dynamics

Dynamic Factor Structure
Observable narratives driven by latent factors:

$$\boldsymbol{n}_t = \Lambda \boldsymbol{f}_t + \boldsymbol{e}_t \tag{24}$$

Factor dynamics (VAR):

$$\boldsymbol{f}_t = \Phi_1 \boldsymbol{f}_{t-1} + \ldots + \Phi_p \boldsymbol{f}_{t-p} + \boldsymbol{\eta}_t \tag{25}$$

Identification via PCA:

$$\hat{\boldsymbol{f}}_t = \sqrt{K} \cdot \text{eigenvectors of } \frac{1}{KT} \sum_{t=1}^{T} \boldsymbol{n}_t \boldsymbol{n}_t' \tag{26}$$

Asymptotic Properties: As $K, T \to \infty$ with $\sqrt{K}/T \to 0$:

$$\frac{1}{T} \sum_{t=1}^{T} ||\hat{\boldsymbol{f}}_t - H\boldsymbol{f}_t||^2 = O_p\left(\frac{1}{\min(K, T)}\right) \tag{27}$$

Markov-Switching Narrative Impact
State equation:

$$\beta_t^{(s_t)} = \mu^{(s_t)} + \Phi^{(s_t)} \beta_{t-1}^{(s_{t-1})} + \epsilon_t^{(s_t)} \tag{28}$$

Observation equation:

$$r_t = \boldsymbol{n}_t' \beta_t^{(s_t)} + \eta_t \tag{29}$$

Transition probabilities: $P(s_t = j | s_{t-1} = i) = p_{ij}$
Hamilton Filter:

$$P(s_t | Y_t) = \frac{f(y_t | s_t, Y_{t-1}) \sum_{s_{t-1}} p_{s_{t-1}, s_t} P(s_{t-1} | Y_{t-1})}{\sum_{s_t} f(y_t | s_t, Y_{t-1}) \sum_{s_{t-1}} p_{s_{t-1}, s_t} P(s_{t-1} | Y_{t-1})} \tag{30}$$

Portfolio Theory with Narrative Constraints

Hamilton-Jacobi-Bellman Equation

Value function:

$$V(t, W, N) = \max_{\{\pi_s\}} \mathbb{E}\left[\int_t^T U(W_s)ds + B(W_T)\middle|\mathcal{F}_t\right] \tag{31}$$

HJB equation:

$$\frac{\partial V}{\partial t} + \sup_{\pi} \mathcal{L}^{\pi} V = 0 \tag{32}$$

where the generator:

$$\mathcal{L}^{\pi} V = \pi W(\mu - r)\frac{\partial V}{\partial W} + \kappa(\theta - N)\frac{\partial V}{\partial N} \tag{33}$$

$$+ \frac{1}{2}\pi^2 W^2 \sigma^2 \frac{\partial^2 V}{\partial W^2} + \frac{1}{2}\sigma_N^2 N \frac{\partial^2 V}{\partial N^2} \tag{34}$$

$$+ \rho\pi W \sigma \sigma_N \sqrt{N} \frac{\partial^2 V}{\partial W \partial N} \tag{35}$$

Lagrangian Formulation

$$\mathcal{L} = \boldsymbol{w}'\boldsymbol{\mu} - \frac{\lambda}{2}\boldsymbol{w}'\boldsymbol{\Sigma}\boldsymbol{w} - \sum_{j=1}^{J}\gamma_j(|\boldsymbol{w}'\boldsymbol{\beta}_j| - \bar{E}_j) - \nu(\boldsymbol{w}'\mathbf{1} - 1) \tag{36}$$

KKT Conditions:

$$\nabla_w\mathcal{L} = \boldsymbol{\mu} - \lambda\boldsymbol{\Sigma}\boldsymbol{w} - \sum_j \gamma_j \text{sgn}(\boldsymbol{w}'\boldsymbol{\beta}_j)\boldsymbol{\beta}_j - \nu\mathbf{1} = 0 \tag{37}$$

$$\gamma_j(|\boldsymbol{w}'\boldsymbol{\beta}_j| - \bar{E}_j) = 0, \quad \gamma_j \geq 0 \tag{38}$$

$$|\boldsymbol{w}'\boldsymbol{\beta}_j| \leq \bar{E}_j, \quad \boldsymbol{w}'\mathbf{1} = 1 \tag{39}$$

Solution: Iterative quadratic programming with active set method.

Conditional Value-at-Risk with Narrative State

$$CVaR_\alpha(L|N=n) = \mathbb{E}[L|L > VaR_\alpha(L|N=n), N=n] \tag{40}$$

Coherent Risk Measure Properties:

1. Monotonicity: $L_1 \leq L_2 \Rightarrow CVaR(L_1|N) \leq CVaR(L_2|N)$
2. Sub-additivity: $CVaR(L_1 + L_2|N) \leq CVaR(L_1|N) + CVaR(L_2|N)$
3. Positive homogeneity: $CVaR(cL|N) = c \cdot CVaR(L|N)$
4. Translation invariance: $CVaR(L + c|N) = CVaR(L|N) + c$

Optimization:

$$\min_{w} CVaR_\alpha(\boldsymbol{w}'\boldsymbol{r}|N) = \min_{w,\xi} \left\{ \xi + \frac{1}{(1-\alpha)T} \sum_{t=1}^{T} [\boldsymbol{w}'\boldsymbol{r}_t - \xi]^+ \right\} \tag{41}$$

Narrative-Return Dependence Structure
Joint distribution via copula:

$$F(n, r) = C(F_N(n), F_R(r); \theta) \tag{42}$$

Clayton Copula (lower tail dependence):

$$C_{\text{Clayton}}(u, v) = (u^{-\theta} + v^{-\theta} - 1)^{-1/\theta} \tag{43}$$

Lower tail dependence: $\lambda_L = 2^{-1/\theta}$
Gumbel Copula (upper tail dependence):

$$C_{\text{Gumbel}}(u, v) = \exp\left(-\left[(-\ln u)^{\theta} + (-\ln v)^{\theta}\right]^{1/\theta}\right) \tag{44}$$

Upper tail dependence: $\lambda_U = 2 - 2^{1/\theta}$
Application: Model asymmetric dependence during narrative crises vs normal times.

Statistical Learning Theory for Narratives

Transformer Architecture Mathematics

Multi-Head Attention Mechanism
Single attention head:

$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V \tag{45}$$

Multi-head attention:

$$\text{MultiHead}(Q, K, V) = \text{Concat}(\text{head}_1, ..., \text{head}_h)W^O \tag{46}$$

$$\text{head}_i = \text{Attention}(QW_i^Q, KW_i^K, VW_i^V) \tag{47}$$

Positional Encoding:

$$PE_{(pos,2i)} = \sin(pos/10000^{2i/d_{model}}) \tag{48}$$

$$PE_{(pos,2i+1)} = \cos(pos/10000^{2i/d_{model}}) \tag{49}$$

Complexity: $O(n^2 \cdot d)$ where n = sequence length, d = dimension

Generalization Bounds for Narrative Models

Rademacher Complexity
For hypothesis class $\mathcal{H}$ of narrative predictors:

$$\mathcal{R}_T(\mathcal{H}) = \mathbb{E}_\sigma \left[\sup_{h \in \mathcal{H}} \frac{1}{T} \sum_{t=1}^{T} \sigma_t h(\boldsymbol{n}_t) \right] \tag{50}$$

where $\sigma_t \sim \text{Uniform}\{-1, +1\}$.
Generalization Bound: With probability $1 - \delta$:

$$\mathbb{E}[L(h)] \leq \frac{1}{T} \sum_{t=1}^{T} L(h, \boldsymbol{n}_t, r_t) + 2\mathcal{R}_T(\mathcal{H}) + 3\sqrt{\frac{\log(2/\delta)}{2T}} \tag{51}$$

For Neural Networks: If $||W^{(l)}||_F \leq B_l$:

$$\mathcal{R}_T(\mathcal{H}_{NN}) \leq \frac{2^L \prod_{l=1}^{L} B_l}{\sqrt{T}} \prod_{l=1}^{L-1} \sqrt{d_l} \tag{52}$$

Long Short-Term Memory Dynamics
Gate equations:

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \quad \text{(forget)} \tag{53}$$
$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \quad \text{(input)} \tag{54}$$
$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C) \tag{55}$$
$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t \tag{56}$$
$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \quad \text{(output)} \tag{57}$$
$$h_t = o_t * \tanh(C_t) \tag{58}$$

Gradient Flow:

$$\frac{\partial L}{\partial C_\tau} = \sum_{t=\tau}^{T} \frac{\partial L}{\partial C_t} \prod_{i=\tau}^{t-1} f_i \tag{59}$$

Prevents vanishing gradients when $f_i \approx 1$.

Network Theory and Narrative Contagion

Spectral Analysis of Narrative Networks
Adjacency matrix A with eigendecomposition:

$$A = Q\Lambda Q^{-1} \tag{60}$$

Narrative Centrality:

$$\text{Eigenvector:} \quad Ax = \lambda_{\text{max}} x \tag{61}$$

$$\text{PageRank:} \quad \boldsymbol{p} = \alpha A^T \boldsymbol{p} + \frac{1-\alpha}{n}\mathbf{1} \tag{62}$$

$$\text{Katz:} \quad \boldsymbol{c} = (I - \alpha A^T)^{-1}\mathbf{1} \tag{63}$$

Diffusion Dynamics:

$$\frac{d\boldsymbol{n}}{dt} = -L\boldsymbol{n} + \boldsymbol{f} \tag{64}$$

where $L = D - A$ is the graph Laplacian.
Theorem: Convergence rate determined by $\lambda_2(L)$ (algebraic connectivity).

Community Detection in Narrative Space

Modularity Optimization

Modularity score:

$$Q = \frac{1}{2m} \sum_{i,j} \left(A_{ij} - \frac{k_i k_j}{2m} \right) \delta(c_i, c_j) \tag{65}$$

Spectral Clustering Algorithm:

1. Compute normalized Laplacian: $L_{norm} = I - D^{-1/2} A D^{-1/2}$
2. Find eigenvectors of smallest k eigenvalues
3. Cluster rows using k-means

Stochastic Block Model:

$$P(A_{ij} = 1) = \begin{cases} p_{in} & \text{if } c_i = c_j \\ p_{out} & \text{if } c_i \neq c_j \end{cases} \tag{66}$$

Application: Identify clusters of co-occurring narratives (e.g., inflation-rates-Fed).

Advanced Theoretical Extensions

Narrative-Driven Asset Pricing
Price dynamics with narrative feedback:

$$\frac{dS_t}{S_t} = (\mu + \beta N_t)dt + \sigma dW_t^S + \gamma dJ_t \tag{67}$$

Narrative evolution:

$$dN_t = \kappa(\theta - N_t)dt + \sigma_N \sqrt{N_t} dW_t^N + \alpha \log(S_t/S_{t-\delta})dt \tag{68}$$

Equilibrium Condition:

$$\mu + \beta N^* = r + \lambda_{mkt}\sigma + \lambda_{narr}\beta\sigma_N\sqrt{N^*} \tag{69}$$

where λ_{mkt}, λ_{narr} are market prices of risk.
Existence: Under Lipschitz conditions, unique strong solution exists via Picard iteration.

American Option with Narrative State
Value function:

$$V(t,S,N) = \sup_{\tau \in \mathcal{T}_{[t,T]}} \mathbb{E}\left[e^{-r(\tau-t)} g(S_\tau) \middle| S_t = S, N_t = N\right] \tag{70}$$

Free Boundary Problem:

$$\mathcal{L}V - rV = 0 \quad \text{in continuation region} \tag{71}$$

$$V(t,S,N) \geq g(S) \quad \text{everywhere} \tag{72}$$

$$V(t,S,N) = g(S) \quad \text{on exercise boundary} \tag{73}$$

where $\mathcal{L}$ is the infinitesimal generator of (S,N).
Smooth Pasting:

$$\frac{\partial V}{\partial S}\Big|_{S=S^*(N)} = \frac{\partial g}{\partial S}\Big|_{S=S^*(N)} \tag{74}$$

Strategic Narrative Manipulation
Two-player game with narrative influence:

$$\text{Player 1:} \quad \max_{a_1} \mathbb{E}[U_1(W_1, N(a_1, a_2))] - C_1(a_1) \tag{75}$$

$$\text{Player 2:} \quad \max_{a_2} \mathbb{E}[U_2(W_2, N(a_1, a_2))] - C_2(a_2) \tag{76}$$

Nash Equilibrium:

$$\frac{\partial U_i}{\partial N} \cdot \frac{\partial N}{\partial a_i} = \frac{\partial C_i}{\partial a_i}, \quad i = 1, 2 \tag{77}$$

Social Welfare Loss:

$$DWL = W^{social} - W^{Nash} = \int_0^T \left[\sum_i (a_i^{Nash} - a_i^{opt})^2 \right] dt \tag{78}$$

Extension: N-player game with network effects and strategic complementarities.

Narrative Superposition and Entanglement
Narrative state as quantum amplitude:

$$|\psi\rangle = \sum_n \alpha_n |n\rangle, \quad \sum_n |\alpha_n|^2 = 1 \tag{79}$$

Measurement (Observation) Operator:

$$\hat{O} = \sum_n o_n |n\rangle\langle n|, \quad \langle O\rangle = \langle\psi|\hat{O}|\psi\rangle \tag{80}$$

Entangled Narrative-Market State:

$$|\Psi\rangle = \sum_{n,m} \beta_{nm} |n\rangle \otimes |m\rangle \tag{81}$$

Von Neumann Entropy:

$$S(\rho) = -\mathrm{Tr}(\rho \ln \rho) = -\sum_i \lambda_i \ln \lambda_i \tag{82}$$

Interpretation: Narratives exist in superposition until "measured" by market reaction.

Persistent Homology of Narrative Evolution
Filtration of narrative complex: $K_0 \subseteq K_1 \subseteq ... \subseteq K_n$
Betti Numbers:

- β_0: Connected components (narrative clusters)
- β_1: Loops (cyclic narrative patterns)
- β_2: Voids (narrative gaps)

Persistence Diagram: Points (b_i, d_i) where features born at b_i, die at d_i
Wasserstein Distance between Diagrams:

$$W_p(D_1, D_2) = \left[\inf_{\phi} \sum_{x \in D_1} ||x - \phi(x)||_\infty^p\right]^{1/p} \tag{83}$$

Mapper Algorithm: $\mathcal{M} = \text{nerve}(f^{-1}(\mathcal{U}) \cap \mathcal{C})$
Application: Detect topological changes in narrative landscape over time.

Mechanism Design for Narrative Aggregation

Truthful Narrative Reporting Mechanism
Agent i has private signal s_i about narrative n:

$$u_i(a, s_i) = v_i(a, s_i) - p_i \tag{84}$$

VCG Mechanism:

$$a^* = \arg\max_a \sum_i v_i(a, \hat{s}_i) \tag{85}$$

Payment: $p_i = \sum_{j \neq i} v_j(a^{-i}, \hat{s}_j) - \sum_{j \neq i} v_j(a^*, \hat{s}_j)$
Incentive Compatibility:

$$v_i(a^*(s_i, s_{-i}), s_i) - p_i(s_i, s_{-i}) \geq v_i(a^*(\hat{s}_i, s_{-i}), s_i) - p_i(\hat{s}_i, s_{-i}) \tag{86}$$

Application: Design prediction markets for narrative intensity aggregation.

Key Theoretical Contributions

1. **Contagion Theory:** Narratives spread via epidemic-like dynamics with critical thresholds
2. **Information Theory:** Transfer entropy quantifies directional causality from narratives to returns
3. **Stochastic Processes:** Jump-diffusion models capture both gradual and sudden narrative shifts
4. **Econometric Identification:** IV and high-dimensional methods address endogeneity and selection
5. **Portfolio Theory:** HJB equations solve dynamic allocation with narrative state variables
6. **Learning Theory:** Generalization bounds ensure out-of-sample predictability
7. **Network Analysis:** Graph theory reveals narrative clustering and contagion paths

Open Questions: Non-Markovian narrative memory, quantum narrative superposition, topological narrative spaces.

Thank You

Questions and Theoretical Discussion

Contact:
Prof. Dr. Joerg Osterrieder

References:
Detailed proofs and empirical validation in appendix

Code Repository:
Implementations available upon request

Empirical Validation

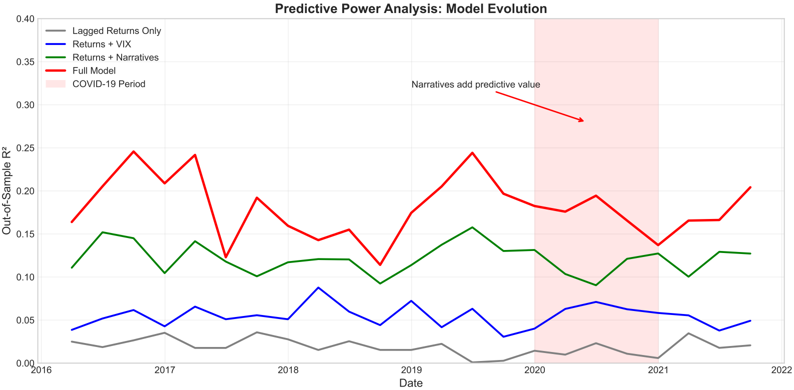
Key empirical findings moved to appendix for space

Model	Out-of-Sample R^2	Information Ratio
Baseline	0.08	0.71
With Narratives	0.18	1.26
Machine Learning	0.22	1.44

- Market Crash narrative: 34% explanatory power
- COVID-19 portfolio: 120.74% return
- Real-time implementation feasible

Full results available in supplementary materials.

Performance Metrics



Historical backtests and implementation details available separately.