How Long Do Markets Need to Fully React to Monetary Policy Announcements?

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Motivation

- News is released $\longrightarrow$ Financial markets react to news
  - If change in price $\approx$ change in expectations $\longrightarrow$ Unanticipated news

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  - Ex: Monetary policy (MP) announcements

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- Useful for empirical macro: Obtain shocks from news to infer causal effects
- Method: High-frequency Identification of MP surprises
  - Measure price change within event window around MP announcement
  - Most popular choice in literature: 30 minutes

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- **Research Q**: What size should the window length around MP announcements be?
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  - Too long: Change in price ≈ MP shocks w/ unrelated news, confounding factors
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  - Just right: Change in price $\approx$ MP shocks with minimised noise
- **Wrong A**: Contributes to MP shocks lacking precision because of noise

This Paper

UAT + Layers

- **This Paper**: Estimate optimal window size for FOMC statements by:
  - Natural language processing (NLP) to combine price dynamics with text-based signal

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1. **Optimal window only**: Noise has min average impact on Δasset prices
2. **Optimal window only**: NLP text-based signal has highest precision
3. **Any other window**: Bad approximation by NLP $\rightarrow$ Bad signal

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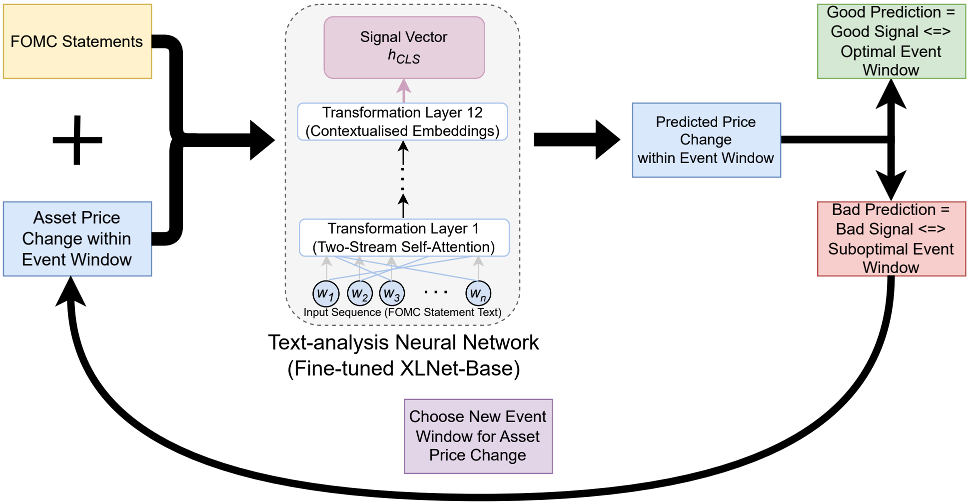

Previous of Results: Summary

FOMC Statement Ex

- **How Long?** Longer than literature standard of 30 minutes:
  - On avg, markets fully react within window 10 min before and 30+ min after
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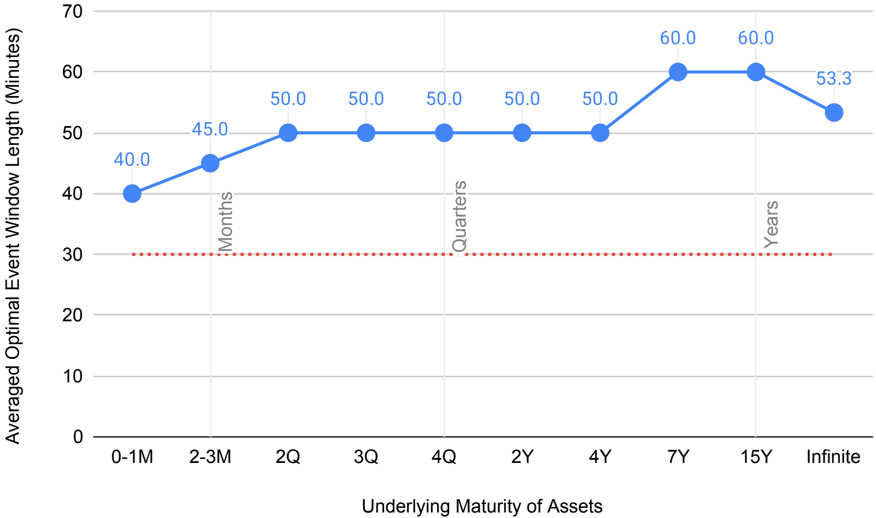
- **Effects on MP**: By changing only event window choice:
  - Underlying maturity of assets ↑, then correlation ↓ between MP surprise sets
  - MP shocks about forward guidance have ↑ impact on yields, inflation, and stock prices
  - MP shocks about forward guidance are ↑ precise on macroeconomic variables

Preview of Results: Visual

Summary Text Summary Table Recap Liquidity



Related Literature and Contributions

1. **Measuring Appropriate Event Window Lengths**
   - Hillmer and Yu (1979); Chang and Chen (1989); Krivin et al. (2003); Das and King (2021); An et al. (2025); Boehm and Kroner (2025); and others...
   - Contributions: (1) If news = text $\rightarrow$ Method can estimate optimal window; (2) Introduce noise min. approach

Related Literature and Contributions

This Paper Results Preview Summary Visual

1. **Measuring Appropriate Event Window Lengths**
2. **Text Analysis in Monetary Policy Communication**
   - Lucca and Trebbi (2009); Hansen and McMahon (2016); Hansen, McMahon, and Prat (2017); Cieslak and Vissing-Jorgensen (2020); Husted et al. (2020); Handlan (2022a); Handlan (2022b); Acosta (2023); Doh et al. (2023); Cieslak and McMahon (2023); Cieslak, Hansen, et al. (2023); Gorodnichenko et al. (2023); Aruoba and Drechsel (2024); Gáti and Handlan (2025a); Gáti and Handlan (2025b); Piller et al. (2025); and others...
   - Contributions: $\uparrow$ adoption of NLP to quantify dimensions of MP communication

Related Literature and Contributions

1. **Measuring Appropriate Event Window Lengths**
2. **Text Analysis in Monetary Policy Communication**
3. **Event Window Lengths in Monetary Policy**
   - Examples: Gürkaynak, Sack, et al. (2005); Gertler and Karadi (2015); Nakamura and Steinsson (2018); Gürkaynak, Kisacikoğlu, et al. (2020); Swanson and Jayawickrema (2023); Handlan (2022b); Bauer and Swanson (2023); An et al. (2025); Boehm and Kroner (2025); and others...
   - Contributions: (1) Optimal window length around FOMC statements $>$ 30-min; (2) different markets, different window lengths; (3) MP effects are amplified and more precise

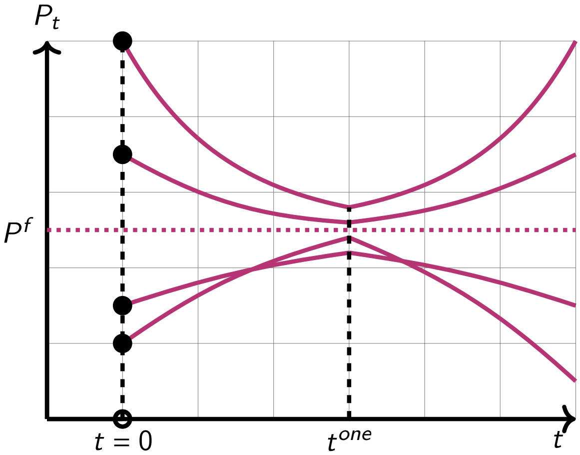
Presentation Roadmap

Motivating Framework of Asset Market Prices

Other Scenarios

$$\{P_t = P_t^f + \varepsilon_t^c + \varepsilon_t^n | t \geq 0\}, \tag{1}$$

- **Fundamental Price**: Constant $\rightarrow P_t^f = P^f \in \mathbb{R}$
  - Price because of news



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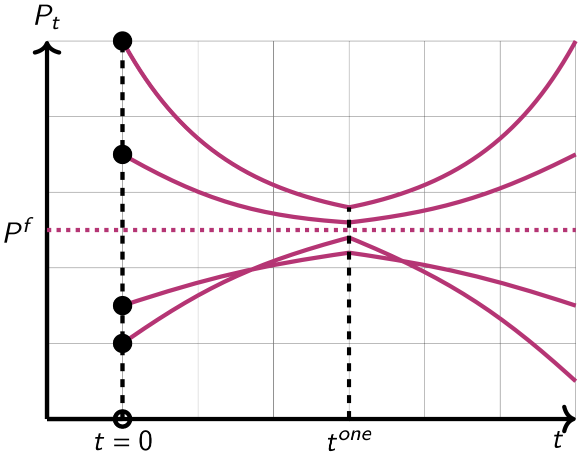
  $\rightarrow \varepsilon_t^c = \rho^c \varepsilon_{t-1}^c + e^{-\mathcal{D}t} \nu_t^c$
  Interpretations
  - $\nu_t^c \sim \mathcal{N}(0, \sigma_c^2)$
  - $|\rho_c| < 1$
  - Decay: $\mathcal{D} \in \mathbb{R}^+$
  - $|\frac{\rho_c}{\mathcal{D}}| < 1$
  - Assumption: $\mathrm{Var}(\varepsilon_0^c) = \sigma_c^2$



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  Interpretations
- **Unrelated News**: Random Walk
  $\longrightarrow \varepsilon_t^n = \varepsilon_{t-1}^n + \nu_t^n$
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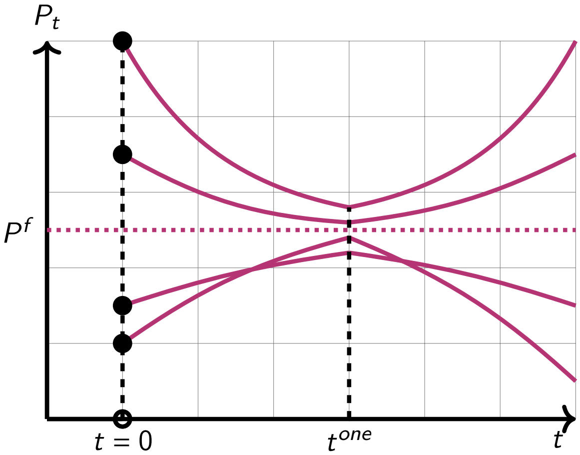
  - Assumption: $\mathrm{Var}(\varepsilon_0^n) = 0$



Single and Multiple News

Single News Derivations Multiple News Derivation

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† I numerically verify the dynamics of the t^{one} for various values of σ_c^2 and σ_n^2 in its indirect expression, holding the other parameters constant.

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  - **Strategy**: Find MSE-minimising time t^* relative to signal $\longrightarrow$ s_i precision matters:

$$t^* : \min_t \frac{1}{N} \sum_{i=1}^{N} (P_{i,t} - s_i)^2 \implies \min_t \left[\frac{1}{N} \sum_{i=1}^{N} \left(\varepsilon_{i,t}^c + \varepsilon_{i,t}^n \right)^2 + \sigma_s^2 \right] \qquad (2)$$

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Motivating Framework Takeaways

Simulation Results

- **Summary**: Always short, always long window → Bad idea
  - "Good" signal → Possible to estimate time horizon reflecting full reactions
- **Constraint**: MP shocks = Finite sample problem → "Good" signal matters

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- **Summary**: Always short, always long window → Bad idea
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- **Constraint**: MP shocks = Finite sample problem → "Good" signal matters
- **Reality**: Do not know noise processes
  - Framework uses strong assumptions to illustrate points
- **Solution**: NLP method estimates optimal window without knowing
  - NLP method can approximate underlying relationship

Presentation Roadmap

Estimating Optimal Event Windows: Method

- **Objective**: Isolate Δasset prices within given window to "full" FOMC statements

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- **Model**: XLNet-Base fine-tuned to approx $f(\text{FOMC Statement}) = \Delta\text{Asset prices}$
  Approach | Input/Output Visual
  - Nonparametric regression approximated by many linear + non-linear combinations
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  - Nonparametric regression approximated by many linear + non-linear combinations
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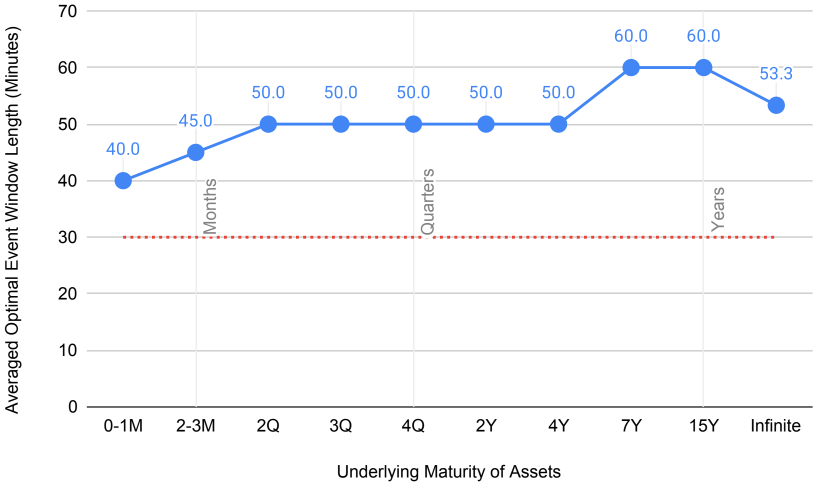
- **Strategy**: Regress Δasset prices in different event windows on FOMC statements CV Strategy | CV Visual | Method "Loop" | Method Visual
  - Pick event window where NN has $\uparrow$ avg out-of-sample predictive performance R^2_{OOS}
  - **Optimal window only**: Noise components have min average impact on Δasset prices

$\Longrightarrow$ "Jointly" estimate optimal window and "good" signal

Optimal Event Windows: Main Results

- **How Long?**

FF3 USc2



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  - OOS predictive quality ≈ NN generalisability ↑ by 2–17% when window ↑ to 40+ min R^2_{OOS}
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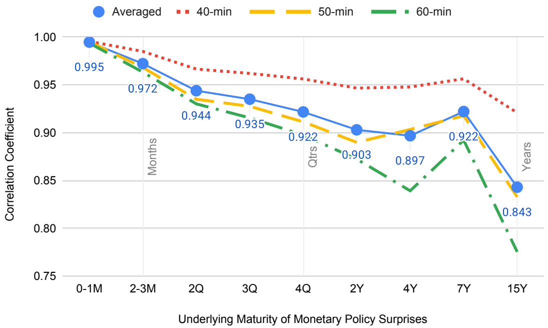
- **Why?** FF3 Scatter USc2 Scatter
  - On avg, markets under-react, ex-post, to FOMC statement within standard windows
  - "Soft" information = Longer to process → Info asymmetry to resolve FOMC Statement Ex
    - Indriawan et al. (2021); Brooks et al. (2023)

Presentation Roadmap

Monetary Policy Surprises: Correlations Along the Yield Curve

Construction Details

- **Methodology:**
  1. Pick optimal window: 40-, 50-, 60-min
  2. Construct MP surprises within 30-min and optimal windows DP → MP Surprise
     - Using FFFs: $mp1, mp2$
     - Using Eurodollar futures: $\Delta ed2, \Delta ed3, \Delta ed4$
     - Using Treasury futures: $\Delta t2, \Delta t5, \Delta t10, \Delta t30$
  3. Calculate correlations between MP surprise sets



- **Result (Figure):**
  - Changing only window length has ↑ effect at farther horizons

Monetary Policy Shocks: Construction Methods

- Focus on median optimal event window length: 50 minutes

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- Use full set of MP surprises as instruments
  - Prevent dampening of MP during ELB period (Brennan et al., 2024; An et al., 2025)

Monetary Policy Shocks: Construction Methods

- Focus on median optimal event window length: 50 minutes
- Use full set of MP surprises as instruments
- Construct MP shocks using diff methods within 30-minutes and optimal windows:
  PCA MP Shock Visuals Summary Stats

  1. Gürkaynak, Sack, et al. (2005):
     - $GSS_T \rightarrow 1^{st}$ Principal component rotated to drive $mp1$
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  2. Nakamura and Steinsson (2018):
     - $NS_{MP} \rightarrow 1^{st}$ Principal component of MP surprises
  3. Jarociński and Karadi (2020):
     - $JK_{MP} \rightarrow 1^{st}$ Principal component of MP surprises w/ SPX + co-movement
     - $JK_{CBI} \rightarrow 1^{st}$ Principal component of MP surprises w/ SPX + co-movement

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- **All shocks scaled**: 1bp ↑ in shock → 1bp ↑ in nominal 1-year Treasury yield

MP Shocks: Effects on Interest Rates, Break-even Inflation, Equities (1/2)

- **LHS Variables**:
  1. ΔTY^i = Daily change in nominal Treasury yields, $i \in \{1, 2, 5, 10\}$
  2. $\Delta TIPS^i$ = Daily change in Treasury Inflation-Protected Security yields, $i \in \{2, 5, 10\}$
  3. ΔBEI^i = Daily change in end-of-day break-even inflation, $i \in \{2, 5, 10\}$
  4. DP_{SPX} = Price log-difference of SPX within 30-minute and optimal windows
  5. DP_{ESc1} = Price log-difference of $ESc1$ within 30-minute and optimal windows
  6. DP_{ESc2} = Price log-difference of $ESc2$ within 30-minute and optimal windows
- **Specification**:

$$y^j = \beta_0^{j,k,l} + \beta_1^{j,k,l}(Shock)^{k,l} + \varepsilon^{j,k,l}, \tag{3}$$

- Shock $k \in \{GSS_T, GSS_P, NS_{MP}, JK_{MP}, JK_{CBI}\}$
- Event window $l \in \{30 \text{ minutes, optimal}\}$

MP Shocks: Effects on Interest Rates, Break-even Inflation, Equities (2/2)

- **Using Optimal Windows**: MP shocks about forward guidance have $\uparrow$ effects on:
  - Nominal interest rates by 8bp on avg Reg Table
  - Real interest rates by 14bp on avg Reg Table
  - Break-even inflation by -5bp on avg Reg Table
  - Stock prices and E-mini futures by 14% on avg Reg Table
- Using non-optimal windows $\rightarrow$ Attenuated MP shock effects on financial variables

MP Shocks: Impulse Responses from Local Projection Approach (1/2)

- **LHS Variables**: Monthly variables i from FRED Summary Stats
  - Log Consumer Price Index (CPI)
  - Log Industrial Production (IP)
  - Nominal 2-year Treasury yield
  - Excess Bond Premium (EBP) (Gilchrist and Zakrajšek, 2012)
- **Specification**: Lag-augmented local projections (Olea and Plagborg-Møller, 2021)

$$y_{t+h}^{i,l} = \theta^{i,k,l}(Shock)_t^{k,l} + controls + \eta^{i,k,l} \tag{4}$$

- Shock $k \in \{GSS_T, GSS_P, NS_{MP}, JK_{MP}, JK_{CBI}\}$
  - All shocks converted to monthly frequency (No meeting $\rightarrow$ Zero shock) Summary Stats
- Event window $l \in \{30 \text{ minutes, optimal}\}$
- **All shocks scaled**: 100bp $\uparrow$ shock $\rightarrow$ Contractionary shock

MP Shocks: Impulse Responses from Local Projection Approach (2/2)

- Calculate confidence interval (CI) widths under 30-minute and optimal windows
  - Average ratio of CI widths: 0.9173 $\rightarrow$ Average CI width $\downarrow$ by 8%
  - Median ratio of CI widths: 0.9410
- **Using Optimal Windows**: Impulse responses of macro variables have $\uparrow$ precision

  LP Visuals
- Using non-optimal windows: Increased noise $\rightarrow$ MP shocks have $\downarrow$ relevancy

Extensions: How do Statement Characteristics Affect Window Length?

- **Question**: Do FOMC statement characteristics affect optimal window length?
- **Approach**: Condition estimation on specific statement features under "One Signal"
  One Signal Approach
- **Findings**: On average, longer windows associated with: FOMC Statement Ex Characteristics
  - More semantically complex statements (Reading Level $\uparrow$) Complexity
  - Statements less similar to previous statement (Cosine Similarity $\downarrow$) Similarity
  - Statements with presence of dissents in the voting record Dissents

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Conclusion

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- **Effects on MP**: By changing only event window choice:
  - Underlying maturity of assets $\uparrow$, then correlation $\downarrow$ between MP surprise sets
    - Correlation can $\downarrow$ as much as 10% for long-maturity assets
  - MP shocks about forward guidance have $\uparrow$ impact on yields, inflation, and stock prices
    - Ex: Average MP shock effect on real interest rates $\uparrow$ by 14bp
  - MP shocks about forward guidance are $\uparrow$ precise on macroeconomic variables
    - Ex: Average impulse response CI width $\downarrow$ by 8%

Next Steps

- **Next steps**:
  1. Estimate optimal event window lengths for other MP communication
     - Ex: Fed Chair and Vice-chair speeches (Swanson and Jayawickrema, 2023)
  2. Analyse how deeper changes in MP communication affect optimal windows
     - Conceptual complexity effect > semantic complexity effect?
  3. Different optimal window lengths for different states?
     - Ex: High/low inflationary periods

Thank you!

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https://paulletran.com/

References I

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Liquidity: Related Symptom for Longer Event Windows (1/2)

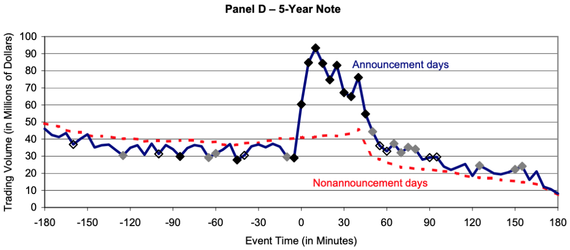
Back to Summary Visual

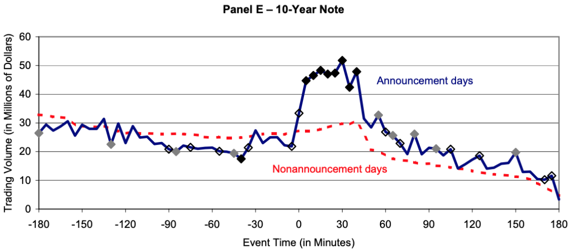
- Do not currently have data access BUT:
  - Fleming and Piazzesi, 2005: ↑ asset horizon, then ↑ time length of abn trading volume
  - Kroner, 2025: Within asset types, futures maturity ↑, then ↓ change in trading volume
- **Both papers**: Document ↑ trading volume on macro news for longer times

→ Assets with ↑ underlying maturities might need more time to fully react

Liquidity: Related Symptom for Longer Event Windows (2/2)

Back to Summary Visual





- Fleming and Piazzesi, 2005

Cognitive Noise Intrepretations

Back to Framework Back to Framework Components

1. Over-reaction: De Bondt and Thaler (1985); La Porta (1996); Antweiler and Frank (2022); Da et al. (2011); Bordalo, Gennaioli, La Porta, et al. (2019); Bordalo, Gennaioli, Ma, et al. (2020); Boguth et al. (2023); Bianchi et al. (2024)
2. Under-reaction: Bernard and Thomas (1989); LKC Chan et al. (1996); WS Chan (2003); Lucca and Moench (2015); Boguth et al. (2023); Bianchi et al. (2024)
3. Noise trading: Bloomfield et al. (2009); Hervé et al. (2019); Ben-David et al. (2022)
4. Algorithmic trading: Caivano (2015); Weller (2017); Gider et al. (2019); Bazzana and Collini (2020); Ben Ammar and Hellara (2022)

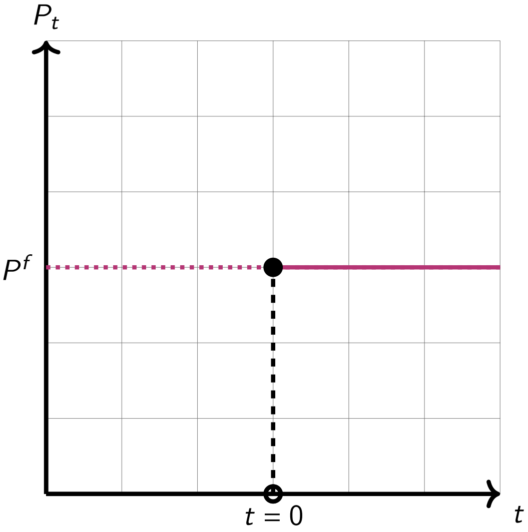
Visualising How Noise Components Affect Prices (1/3)

Back to Framework

No cognitive noise + No unrelated news

- $P_t \rightarrow P^f$ because of no cognitive noise
- P_t moves anywhere over time because of unrelated news

$\longrightarrow$ Choose shortest event window



Visualising How Noise Components Affect Prices (2/3)

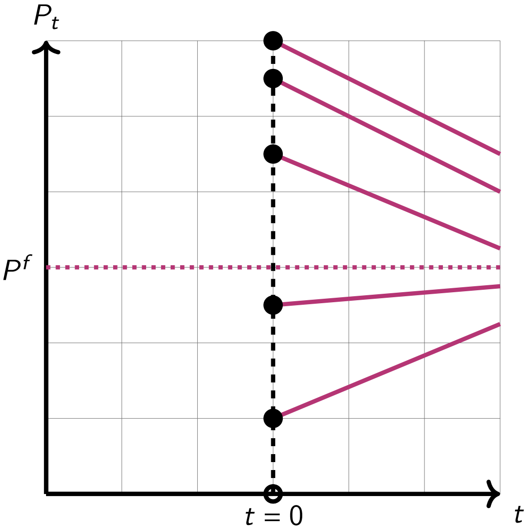
Back to Framework

Cognitive noise + No unrelated news

Interpretations

- P_t jumps anywhere because of cognitive noise
- $P_t \rightarrow P^f$ because of no unrelated news

$\rightarrow$ Choose long event window

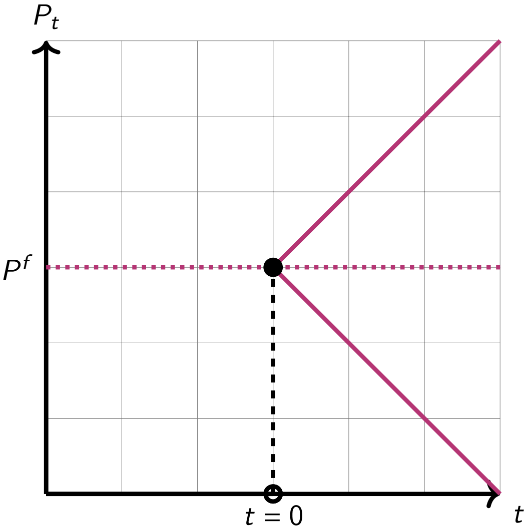


Visualising How Noise Components Affect Prices (3/3)

Back to Framework

No cognitive noise + Unrelated news

- $P_t \to P^f \because$ no cognitive noise
- P_t moves anywhere over time $\because$ unrelated news
- $\therefore$ Choose short event window



Derivation of $\mathrm{Var}(P_t|t \geq 0)$ and $\frac{\partial \mathrm{Var}(P_t|t\geq 0)}{\partial t}$ (1/3)

Back

$$
\begin{aligned}
\mathrm{Var}(P_0) &= \mathrm{Var}(\varepsilon_0^c) + \mathrm{Var}(\varepsilon_0^n) \\
&= \sigma_c^2 \\
\mathrm{Var}(P_1) &= \mathrm{Var}(\varepsilon_1^c) + \mathrm{Var}(\varepsilon_1^n) \\
&= \sigma_c^2(\rho_c^2 + e^{-2\mathcal{D}}) + \sigma_n^2 \\
\mathrm{Var}(P_2) &= \mathrm{Var}(\varepsilon_2^c) + \mathrm{Var}(\varepsilon_2^n) \\
&= \sigma_c^2(\rho_c^4 + \rho_c^2 e^{-2\mathcal{D}} + e^{-4\mathcal{D}}) + 2\sigma_n^2 \\
&\ \ \vdots \\
\mathrm{Var}(P_t|t \geq 0) &= \left[\sum_{i=0}^{t} \rho_c^{2(t-i)} e^{-2\mathcal{D}i}\right] \sigma_c^2 + t\sigma_n^2 \\
\implies \mathrm{Var}(P_t|t \geq 0) &= \left[\frac{\rho_c^{2(t+1)} - e^{-2(t+1)\mathcal{D}}}{\rho_c^2 - e^{-2\mathcal{D}}}\right] \sigma_c^2 + t\sigma_n^2
\end{aligned}
$$

Derivation of $\mathrm{Var}(P_t|t \geq 0)$ and $\frac{\partial \mathrm{Var}(P_t|t \geq 0)}{\partial t}$ (2/3)

Back

$$\mathrm{Var}(P_t|t \geq 0) = \left[\frac{\rho_c^{2(t+1)} - e^{-2(t+1)\mathcal{D}}}{\rho_c^2 - e^{-2\mathcal{D}}}\right]\sigma_c^2 + t\sigma_n^2$$

$$\frac{\partial \mathrm{Var}(P_t|t \geq 0)}{\partial t} = \left\{\frac{2\left[ln(\rho_c)\rho_c^{2(t+1)} + \mathcal{D}\left[(e^{-2(t+1)\mathcal{D}}\right]\right]}{\rho_c^2 - e^{-2\mathcal{D}}}\right\}\sigma_c^2 + \sigma_n^2$$

Derivation of $\mathrm{Var}(P_t|t \geq 0)$ and $\frac{\partial \mathrm{Var}(P_t|t\geq 0)}{\partial t}$ (3/3)

Back

$$\mathrm{Var}(P_t|t \geq 0) = \overbrace{\left[\frac{\rho_c^{2(t+1)} - e^{-2(t+1)\mathcal{D}}}{\rho_c^2 - e^{-2\mathcal{D}}}\right]}^{\lim_{t\to\infty} \text{ is } 0} \sigma_c^2 + t\sigma_n^2 \tag{5}$$

Derivation of $\mathrm{Var}(P_t|t \geq 0)$ and $\frac{\partial \mathrm{Var}(P_t|t\geq 0)}{\partial t}$ (3/3)

Back

$$\mathrm{Var}(P_t|t \geq 0) = \overbrace{\left[\frac{\rho_c^{2(t+1)} - e^{-2(t+1)\mathcal{D}}}{\rho_c^2 - e^{-2\mathcal{D}}}\right]}^{\lim_{t\to\infty} \text{ is } 0} \sigma_c^2 + t\sigma_n^2 \tag{5}$$

$$\Longrightarrow t^{one} : \mathcal{D}\left[e^{-2(t+1)\mathcal{D}}\right] + ln(\rho_c)\rho_c^{2(t+1)} = \left[\frac{(e^{-2\mathcal{D}} - \rho_c^2)}{2}\right]\frac{\sigma_n^2}{\sigma_c^2} \tag{6}$$

Derivation of $\mathrm{Var}(P_t|t \geq 0)$ and $\frac{\partial \mathrm{Var}(P_t|t\geq 0)}{\partial t}$ (3/3)

Back

$$\mathrm{Var}(P_t|t \geq 0) = \overbrace{\left[\frac{\rho_c^{2(t+1)} - e^{-2(t+1)\mathcal{D}}}{\rho_c^2 - e^{-2\mathcal{D}}}\right]}^{\lim_{t\to\infty} \text{ is } 0} \sigma_c^2 + t\sigma_n^2 \tag{5}$$

$$\implies t^{one} : \mathcal{D}\left[e^{-2(t+1)\mathcal{D}}\right] + ln(\rho_c)\rho_c^{2(t+1)} = \left[\frac{(e^{-2\mathcal{D}} - \rho_c^2)}{2}\right]\frac{\sigma_n^2}{\sigma_c^2} \tag{6}$$

$$\implies \frac{\partial t^{one}}{\partial \sigma_n^2} < 0, \frac{\partial t^{one}}{\partial \sigma_c^2} > 0^{\ddagger}$$

‡Because Equation 3 is unable to have t isolated on one side, I numerically verify the dynamics of the t^{one} for various values of σ_c^2 and σ_n^2 in the indirect expression whilst holding the other parameters constant.

Derivation of MSE Minimisation Problem with Signal

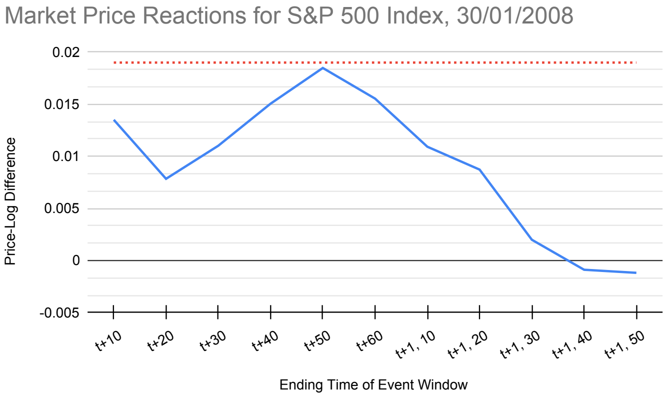
Back

$$
\begin{aligned}
t^* : \min_t \frac{1}{N}\sum_{i=1}^{N}\left(P_{i,t} - s_i\right)^2 &= \min_t \frac{1}{N}\sum_{i=1}^{N}\left(P_i^f + \varepsilon_{i,t}^c + \varepsilon_{i,t}^n - P_i^f - \xi_i\right)^2 \\
&= \min_t \frac{1}{N}\sum_{i=1}^{N}\left(\varepsilon_{i,t}^c + \varepsilon_{i,t}^n - \xi_i\right)^2 \\
&= \min_t \frac{1}{N}\sum_{i=1}^{N}\left[\left(\varepsilon_{i,t}^c + \varepsilon_{i,t}^n\right)^2 + \xi_i^2 - 2\xi_i\left(\varepsilon_{i,t}^c + \varepsilon_{i,t}^n\right)\right] \\
&= \min_t \left\{\mathbb{E}\left[\left(\varepsilon_{i,t}^c + \varepsilon_{i,t}^n\right)^2\right] + \mathbb{E}\left[\xi_i^2\right] - 2\,\mathbb{E}\left[\xi_i\right]\mathbb{E}\left[\left(\varepsilon_{i,t}^c + \varepsilon_{i,t}^n\right)\right]\right\} \\
\implies t^* : \min_t \frac{1}{N}\sum_{i=1}^{N}\left(P_{i,t} - s_i\right)^2 &= \min_t \left[\frac{1}{N}\sum_{i=1}^{N}\left(\varepsilon_{i,t}^c + \varepsilon_{i,t}^n\right)^2 + \sigma_s^2\right] \qquad (7)
\end{aligned}
$$

Multiple News: Example of Signal in Financial Prices

Back

- **Red Dotted Line**: Signal (s_i) $\approx$ Fundamental price change because of news
- **Blue Line**: Observed price change with varying noise levels
- **Optimisation**: t^* is where signal best represents observed price change



Simulation Setup (1/3): Initial Conditions

Back

- $t = 0$: Release of one FOMC announcement
  - $P^f_{t,i} = P^f_i \in [-100, 100]$
  - $\varepsilon^c_{i,0} \in [-100, 100]$
  - $\varepsilon^n_{i,0} = 0$
  - $\sigma_s \in \mathbb{R}$

Simulation Setup (2/3): MSEs

Back

- For single news $i \in N = 10,000$:
  - Simulate $P_{i,t}$ (and components) and s_i up to $t = 100$
  - Calculate $\left(P_{i,t} - P^f_{i,t}\right)^2$ and $\left(P_{i,t} - s_i\right)^2$
- Across all N news:
  - Calculate MSEs $\sum_{i=1}^{N} \frac{1}{N} \left(P_{i,t} - P^f_{i,t}\right)^2$ and $\sum_{i=1}^{N} \frac{1}{N} \left(P_{i,t} - s_{i,t}\right)^2$
  - Calculate t^* and $\hat{t}$

Simulation Setup (3/3): Market Scenarios

Back

- Calculate $t^*, \hat{t}$ under 3 asset market scenarios:

	Scenario 1	Scenario 2	Scenario 3
P_i^f	$\in [-100, 100]$	$\in [-100, 100]$	$\in [-100, 100]$
$\varepsilon_{i,0}^c$	$\in [-100, 100]$	$\in [-100, 100]$	$\in [-100, 100]$
$\varepsilon_{i,0}^n$	0	0	0
σ_c	100	0.1	50
$\mathcal{D}$	0.5	1	0.75
σ_n	0.1	10	1
ρ_c	0.47	0.47	0.47
σ_s	$\in \mathbb{R}$	$\in \mathbb{R}$	$\in \mathbb{R}$

Table 1: Framework Parameters for Simulations

- Scenario 1 ~ High presence of cognitive noise, little unrelated news
- Scenario 2 ~ Little cognitive noise, high presence of unrelated news
- Scenario 3 ~ Presence of both cognitive noise and unrelated news

Simulation Results

Back

	Scenario 1	Scenario 2	Scenario 3
Simulation Parameters			
P_i^f	$\in [-100, 100]$	$\in [-100, 100]$	$\in [-100, 100]$
$\varepsilon_{i,0}^c$	$\in [-100, 100]$	$\in [-100, 100]$	$\in [-100, 100]$
$\varepsilon_{i,0}^n$	0	0	0
σ_c	100	0.1	50
$\mathcal{D}$	0.5	1	0.75
σ_n	0.1	10	1
ρ_c	0.47	0.47	0.47
σ_s	$\in \mathbb{R}$	$\in \mathbb{R}$	$\in \mathbb{R}$
Simulation Results			
t^*	16	2	10
$\hat{t}$	15	2	10

Table 2: Framework Parameters and Results from 10,000 Simulations

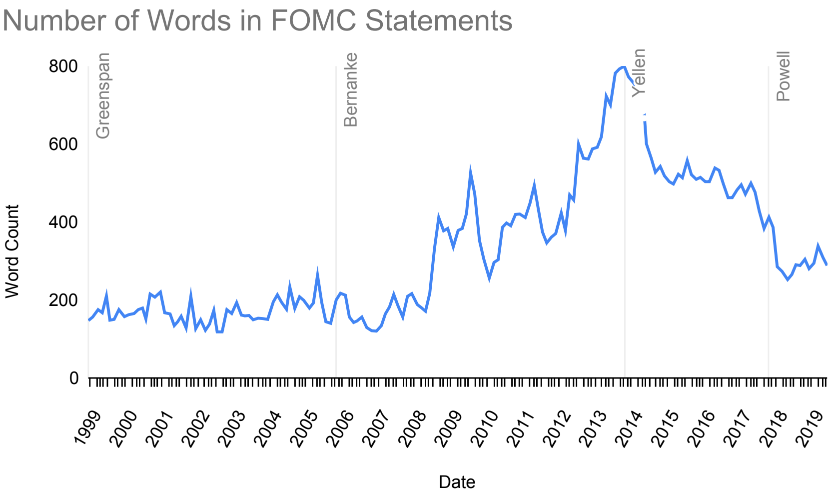
Preprocessing FOMC Statement Text

Back to Method

- Remove:
  - URLs and hyperlinks from statement's HTML file
  - FOMC member voting record from end of statement
  - List of regional bank request approvals
  - Release timestamp (e.g., "For immediate release")
- Change:
  - Statement file type to text
  - Text coding into standardised UTF-8 format (e.g., change length of "-")
  - Spacing between words to be one space

Preprocessed FOMC Statement Length

Back to Method



Cleaned FOMC Statement (08/2011) (1/3)

1. Information received since the Federal Open Market Committee met in June indicates that economic growth so far this year has been considerably slower than the Committee had expected.
2. Indicators suggest a deterioration in overall labor market conditions in recent months, and the unemployment rate has moved up.
3. Household spending has flattened out, investment in nonresidential structures is still weak, and the housing sector remains depressed.
4. However, business investment in equipment and software continues to expand.
5. Temporary factors, including the damping effect of higher food and energy prices on consumer purchasing power and spending as well as supply chain disruptions associated with the tragic events in Japan, appear to account for only some of the recent weakness in economic activity.
6. Inflation picked up earlier in the year, mainly reflecting higher prices for some commodities and imported goods, as well as the supply chain disruptions.

Cleaned FOMC Statement (08/2011) (2/3)

1.
2. More recently, inflation has moderated as prices of energy and some commodities have declined from their earlier peaks. Longer-term inflation expectations have remained stable.
3. Consistent with its statutory mandate, the Committee seeks to foster maximum employment and price stability.
4. The Committee now expects a somewhat slower pace of recovery over coming quarters than it did at the time of the previous meeting and anticipates that the unemployment rate will decline only gradually toward levels that the Committee judges to be consistent with its dual mandate.
5. Moreover, downside risks to the economic outlook have increased.
6. The Committee also anticipates that inflation will settle, over coming quarters, at levels at or below those consistent with the Committee's dual mandate as the effects of past energy and other commodity price increases dissipate further.
7. However, the Committee will continue to pay close attention to the evolution of inflation and inflation expectations.

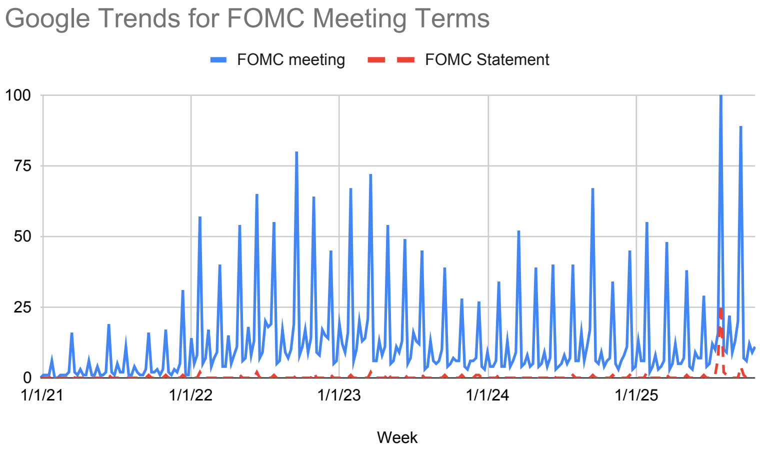
Cleaned FOMC Statement (08/2011) (3/3)

1. To promote the ongoing economic recovery and to help ensure that inflation, over time, is at levels consistent with its mandate, the Committee decided today to keep the target range for the federal funds rate at 0 to 1/4 percent.
2. The Committee currently anticipates that economic conditions–including low rates of resource utilization and a subdued outlook for inflation over the medium run–are likely to warrant exceptionally low levels for the federal funds rate at least through mid-2013.
3. The Committee also will maintain its existing policy of reinvesting principal payments from its securities holdings.
4. The Committee will regularly review the size and composition of its securities holdings and is prepared to adjust those holdings as appropriate.
5. The Committee discussed the range of policy tools available to promote a stronger economic recovery in a context of price stability.
6. It will continue to assess the economic outlook in light of incoming information and is prepared to employ these tools as appropriate.

Why FOMC Statements?

Back to Method

- FOMC statements = Initial + Primary communication of MP
  - FOMC statement website = $1^{st} - 3^{rd}$ query on search engines



Output: Interest-rate and Equity Futures

Back to Method

- **Output**: $DP_{t+n} = ln\left(\frac{P_{t+n}}{P_{t-10}}\right)$ for interest-rate and equity futures Futures Overview
  - Price levels at 10-min-intervals: 10 min before to 18 hours after statement release
  - Fed Fund Futures: $FF1, FF2, FF3, FF4$
  - Eurodollar Futures: $EDcm2, EDcm3, EDcm4$
  - 2-Year Treasury Futures: $TUc1, TUc2$
  - 5-Year Treasury Futures: $FVc1, FVc2$
  - 10-Year Treasury Futures: $TYc1,\ TYc2$
  - 30-year Treasury Futures: $USc1, USc2$
  - S&P 500 Index and E-mini Futures: $SPX, ESc1, ESc2$

Futures Contract Overview (1/2)

Back to Futures List

- Federal Fund futures: For a given expiry month, on last day of expiry month, contract pays out 100 minus the average federal funds rate over the final month
- Eurodollar futures: Quarterly contracts which pay out 100 minus the 3-month US dollar British Banks Association London Interbank Offered Rate (BBA LIBOR) interest rate at the time of expiry month (i.e., March, June, September, and December).
- 2-year Treasure futures: Quarterly contracts that obligate seller to deliver Treasury notes within a range of maturities up to 2 years on the last day of the expiry month to the buyer (i.e., March, June, September, and December). Average maturity is 2 years (Gürkaynak, Kisacikoğlu, et al., 2020)
- 5-year Treasure futures: Quarterly contracts that obligate seller to deliver Treasury notes within a range of maturities up to 5 years on the last day of the expiry month to the buyer (i.e., March, June, September, and December). Average maturity is 4 years (Gürkaynak, Kisacikoğlu, et al., 2020)

Futures Contract Overview (2/2)

Back to Futures List

- 10-year Treasure futures: Quarterly contracts that obligate seller to deliver Treasury notes within a range of maturities up to 10 years on the last day of the expiry month to the buyer (i.e., March, June, September, and December). Average maturity is 7 years (Gürkaynak, Kisacikoğlu, et al., 2020)
- 30-year Treasure futures: Quarterly contracts that obligate seller to deliver Treasury notes within a range of maturities up to 30 years on the last day of the expiry month to the buyer (i.e., March, June, September, and December). Average maturity is 15 years (Gürkaynak, Kisacikoğlu, et al., 2020)
- S&P 500 E-mini futures: Quarterly contracts that pay out 50 USD $\times$ S&P 500 value on the last day of the expiry month (i.e., March, June, September, and December)

NN Input/Output Visual

Back to Method

- Each FOMC statement is paired with DP_{t+n} for each asset
- Input $X_i = 768 \times j$ matrix: Columns $=$ j words in order, rows $=$ 768 word-features

Statement Text	Dec 12, 2006: "The Federal Open Market Committee decided today to keep its target for the federal funds rate at 5 1/4 percent..."
Input Matrix 768 word-features $\times$ 512 words	$\left[\underbrace{x_i^1}_{\textit{The}} \; \underbrace{x_i^2}_{\textit{Federal}} \; \underbrace{x_i^3}_{\textit{Open}} \; \underbrace{x_i^4}_{\textit{Market}} \; \underbrace{x_i^5}_{\textit{Committee}} \; \underbrace{x_i^6}_{\textit{decided}} \; \ldots \; \underbrace{x_i^{512}}_{.}\right]$

- x_t^0 = Dummy vector that gets updated with intermediate layers of X
- Output $=$ $DP_{i,t+n}$ for each asset
- Update XLNet-Base parameters to minimise $\sum_{i \in N} \frac{1}{N} \left(DP_{i,t+n} - \widehat{DP}_{i,t+n}\right)^2$

Popular Text Analysis Methods in Macro

Back to Approach

1. Counts of single words
   - "employment went up, but inflation did not"
   - "inflation went up, but employment did not"
   - **Problem**: Method produces same measure from both sentences
2. Counts of n-grams
   - "economic growth slowed, but is expected to pick up pace later this year"
   - **Problem**: Method doesn't quantify full sentence context

Estimating Optimal Event Windows: Approach

Back to Method

- **At the Core**: $f(\text{FOMC statement text}) = DP_{t+n}$: Nonparametric mapping

Estimating Optimal Event Windows: Approach

Back to Method

- **At the Core**: f(FOMC statement text) = DP_{t+n}: Nonparametric mapping
- Popular text analysis methods in empirical macro:
  - "Fitting predictive models on simple counts of text features" (Gentzkow et al., 2019)

Estimating Optimal Event Windows: Approach

Back to Method

- **At the Core**: f(FOMC statement text) = DP_{t+n}: Nonparametric mapping
- Popular text analysis methods in empirical macro:
  - "Fitting predictive models on simple counts of text features" (Gentzkow et al., 2019)
- Popular methods cannot realistically: Popular Method Ex Issues
  - Quantify all info. in text (e.g., Word interdependencies, context, long-term memory)

$\Longrightarrow$ Approximate f(FOMC statement text) = DP_{t+n}

Estimating Optimal Event Windows: Approach

Back to Method

- **At the Core**: f(FOMC statement text) = DP_{t+n}: Nonparametric mapping
- Popular methods cannot quantify f(FOMC statement text) = DP_{t+n}
- **Foundation**: Text-analysis neural network XLNet-Base (Yang et al., 2019) can:
  - Transfer learning: Fine-tune pre-trained XLNet-Base on FOMC language
  - Features: Bi-directional learning, recurrent memory, permutation modelling

UAT + Layers XLNet-Base Details Addressing Look-ahead Bias

$\Longrightarrow$ "Good" signal based on FOMC statement text within given window length

$\Longrightarrow$ "Jointly" estimate optimal window and "good" signal

Universal Approximation Theorem

Back to This Paper Back to Approach Back to NN Training Overview

- Universal Approximation Theorem (Hornik et al., 1989; and others...) from ML literature:
  - Neural networks with at least 1 hidden layer can approximate any function
  - Existence theorem $\rightarrow$ Nothing about finding structure and training
- In reality, adding more layers:
  - $\downarrow$ number of parameters for each node function
  - $\downarrow$ computational, data, and training requirements

Details about XLNet-Base from Yang et al. (2019)

Hyperparameters Back to Approach

- **Overview**: Open-source, pretrained NN for text analysis
  - Paper version: XLNet-Base
- **Design**: Permutation- and autoregressive-based learning
  - 12 hidden layers (each of size 768)
  - 12 self-attention heads (each of size 64)
  - Vocabulary size of 32,000 word tokens
  - 110 million network parameters
- **Text Input**: Sequence of numerical vectors representing words and document
- **Transfer Learning**: "pretrained" parameters = Starting point for new task
  - SOTA status in translation, Q&A, word prediction, classification/regression
- **Initial Task**: Predict words using all permutations of text
- **Initial Data**: BookCorpus (11,038 books), English Wikipedia (6 mil articles)
  - Additional data for original, larger-scale NN:
    - Giga5 (9.9 mil news articles), ClueWeb12 (733 mil web pages), Common Crawl (1K+ TB text from web pages)

Hyperparameters for Fine-tuning XLNet-Base (1/2)

XLNet-Base Details

Hyperparameter	Value
Number of Layers	12
Hidden Size	768
Number of Attention Heads	12
Attention Head Size	64
Hidden Dropout	0.1
Attention Dropout	0.1
Max Sequence Length	512
Vocab Size	32,000

Table 3: The symbol "*" denotes the hyperparameter that undergoes tuning during the fine-tuning process. The random seed is set as a constant to ensure replicability by always initalising random components (e.g., weights and biases) to the same value. (cont.)

Hyperparameters for Fine-tuning XLNet-Base (2/2)

XLNet-Base Details

Hyperparameter	Value
Training Batch Size	8
Evaluation Batch Size	8
Max Num of Steps	2040
Max Num of Epochs	120
Manual Random Seed	47
Learning Rate	*
Warmup Ratio	0.06
Adam Epsilon	1e-8
Learning Rate Decay	Linear

Table 4: The symbol "*" denotes the hyperparameter that undergoes tuning during the fine-tuning process. The random seed is set as a constant to ensure replicability by always initalising random components (e.g., weights and biases) to the same value.

Addressing Look-ahead Bias

Back to Approach Back to Loop

- Sarkar and Vafa (2024): NNs predict values in past using info. in the future.
  - NNs for text analysis trained with large amounts of data
  - High probability of future info. used in initial training of NN weights
  - Look-ahead bias addressed for 2 reasons:

1. XLNet-Base initially trained only with BookCorpus and English Wikipedia
   - Very low probability of XLNet-Base initially trained on FOMC statements and futures data
2. Pre-processed FOMC statements have no references to relevant times t and $t+1$

XLNet-Base Details

Estimating Optimal Event Windows: Prepare for Train + Eval XLNet

Back

- **Goal**: "Good" signal from XLNet-Base for every FOMC statements
  - Method from ML literature: Train XLNet-Base on splits of data

Estimating Optimal Event Windows: Prepare for Train + Eval XLNet

Back

- **Goal**: "Good" signal from XLNet-Base for every FOMC statements
  - Method from ML literature: Train XLNet-Base on splits of data
- Split data into training (80%) and testing (20%) samples 5 times:
  - By stratified sampling Why Stratified? Why CV?
  - Conditions: Word count (200-word bins), FFR decision, FOMC chair, pre/post 2007
  - Every testing subsample share NO FOMC statements

Estimating Optimal Event Windows: Prepare for Train + Eval XLNet

Back

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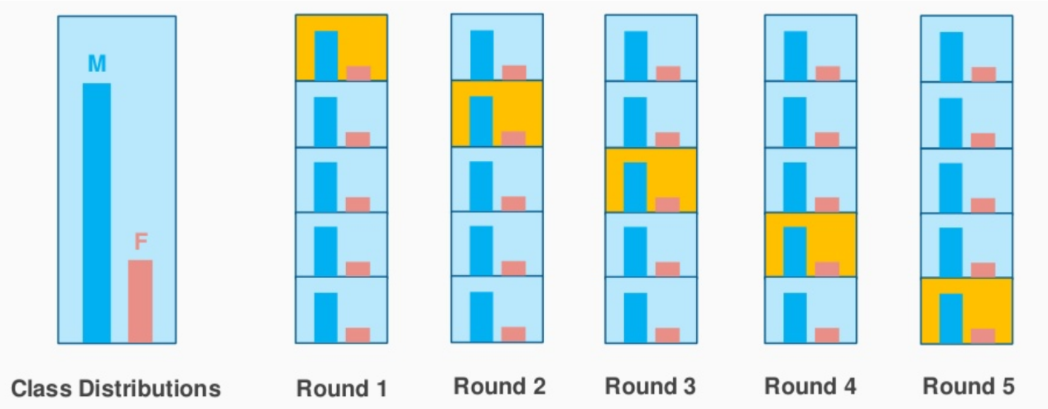
    Why Stratified? Why CV?
  - Conditions: Word count (200-word bins), FFR decision, FOMC chair, pre/post 2007
  - Every testing subsample share NO FOMC statements
- **Result**: XLNet-Base learns $f(\text{FOMC statement text}) = DP_{t+n}$ for each fold:
  - With equal distribution of FOMC statements based on characteristics

Estimating Optimal Event Windows: Stratified CV Visual

Back to Method



Estimating Optimal Event Windows: Method "Loop"

Back to Method

For each interest-rate and equity futures contract:

Estimating Optimal Event Windows: Method “Loop”

Back to Method

For each interest-rate and equity futures contract:

- For each DP_{t+n} up to $t + 60$:

Estimating Optimal Event Windows: Method "Loop"

Back to Method

For each interest-rate and equity futures contract:

- For each DP_{t+n} up to $t+60$:
  - For each split:
  1. Fine-tune NN parameters and hyperparameters to fit training data
     NN Training Overview Hyperparameter Tuning Addressing Look-ahead Bias
  2. Evaluate NN on testing data $\rightarrow$ Choose hyperparameters that yield highest R^2_{OOS}

Estimating Optimal Event Windows: Method "Loop"

Back to Method

For each interest-rate and equity futures contract:

- For each DP_{t+n} up to $t+60$:
  - For each split:

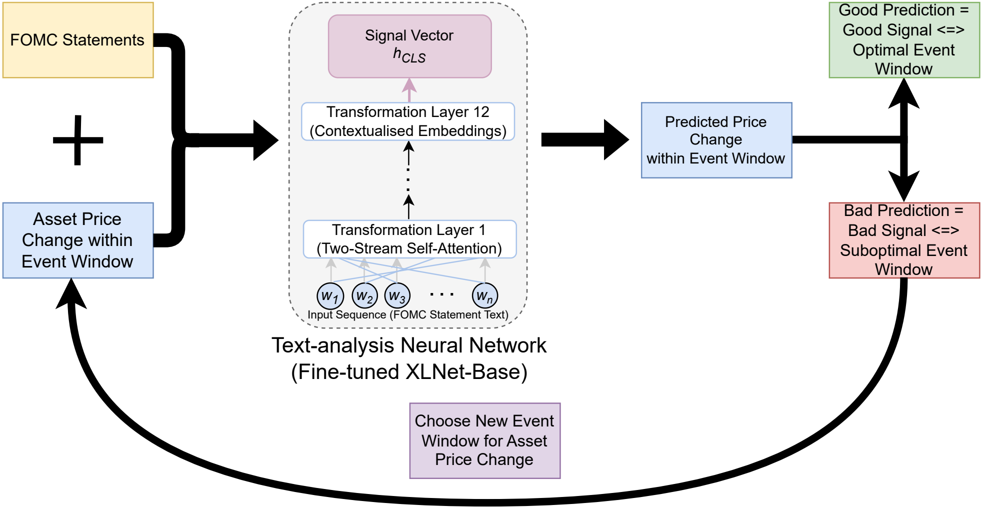
1. Fine-tune NN parameters and hyperparameters to fit training data

NN Training Overview Hyperparameter Tuning Addressing Look-ahead Bias

2. Evaluate NN on testing data $\longrightarrow$ Choose hyperparameters that yield highest R^2_{OOS}
3. **Final Output**: $\overline{R^2_{OOS}} := R^2_{OOS}$ averaged across 5 splits
   - Other R^2_{OOS} metrics: Min, max, $75^{th}, 25^{th}$ percentiles

Estmating Optimal Event Windows: Method Visual

Back to Method



NN Training Overview

Back to Loop

- Train NN → Fine-tune parameters and hyperparameters to fit training data Small NN Ex

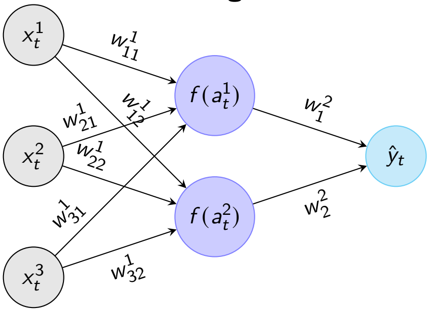
  1. Fix network structure (layers and nodes) + non-tuned hyperparameters UAT + Layers
  2. Choose value for hyperparameter that will be tuned Hyperparameter Tuning
  3. Iteratively update parameters to $\downarrow \widehat{MSE_{IS}}$
  4. Evaluate NN → Judge based on R^2_{OOS}
  5. Poor performance → Go back to step 1

Small NN Example

Back to NN Training Overview

- **Data:** 4 variables x_t^1, x_t^2, x_t^3, y_t
- **Goal:** Predict y_t from $X \equiv x_t^1, x_t^2, x_t^3$
- **Example:** 2 layers, 2 "hidden" nodes
- From X_t to $\hat{y}_t$ for observation $t \in T$:
  - Linearly combine $x_t^1, x_t^2, x_t^3 \rightarrow a_t^1, a_t^2$
  - f is a non-linear function
  - $\hat{y}_t$ is predicted output
- **Training** prediction error $\rightarrow$ update weights w
- **Testing** prediction error $\rightarrow$ update network structure

NN Figure



NN Matrix Algebra

$$\begin{bmatrix} x_t^1 & x_t^2 & x_t^3 \end{bmatrix} \begin{bmatrix} w_{11}^1 & w_{12}^1 \\ w_{21}^1 & w_{22}^1 \\ w_{31}^1 & w_{32}^1 \end{bmatrix} = \begin{bmatrix} a_t^1 & a_t^2 \end{bmatrix}$$

$$\begin{bmatrix} f(a_t^1) & f(a_t^2) \end{bmatrix} \begin{bmatrix} w_1^2 \\ w_2^2 \end{bmatrix} = \hat{y}_t$$

Why Stratified Sampling?

Back to CV

- Why stratified over random splitting?
  1. Transfer learning $\longrightarrow$ Lower data requirements for NNs BUT
  2. Large sample size for NNs $\longrightarrow$ Fold $\approx$ Population for characteristics
     $\longrightarrow$ Can use random k-fold cross validation
  3. Finite sample size for NNs $\nrightarrow$ Fold $\approx$ Population
     – Create folds conditioned on class dist can help
  4. Minimises diff between pop and fold distributions of FOMC statement characteristics
  5. **Result**: Better learning and predictive performance from NN

Estimating Optimal Event Windows: Accuracy Metrics

Back to Method

- For each split, primary metric to judge NN = generalised $R^2 := R^2_{OOS}$ R^2 Details
- Make adjustments from typical definition because:

Estimating Optimal Event Windows: Accuracy Metrics

Back to Method

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Estimating Optimal Event Windows: Accuracy Metrics

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- Make adjustments from typical definition because:
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- **Other Tracked Metrics**: ρ_{OOS}, $\widehat{MAE}_{OOS}$, $\widehat{MSE}_{IS}$

Estimating Optimal Event Windows: Accuracy Metrics

Back

- For each fold, primary metric to judge NN from Hawinkel et al. (2024):

$$R^2_{OOS} = 1 - \frac{\widehat{MSE}}{\widehat{MST}} = 1 - \frac{T^{-1}\sum_{i=1}^{T}(y_i - \hat{y}_i)^2}{\frac{T+1}{T(T-1)}\sum_{i=1}^{T}(y_i - \overline{y_{IS}})^2}, \tag{8}$$

Estimating Optimal Event Windows: Accuracy Metrics

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Estimating Optimal Event Windows: Accuracy Metrics

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Estimating Optimal Event Windows: Accuracy Metrics

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Estimating Optimal Event Windows: Accuracy Metrics

Back

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- **Explicit objective function**: Minimise $\widehat{MSE}$ during fine-tuning
  - $\min \widehat{MSE} = \max R^2_{OOS}$
- **Other tracked metrics**: ρ_{OOS}, $\widehat{MAE}_{OOS}$, $\widehat{MSE}_{IS}$

Why Cross Validation?

Back to Stratified CV

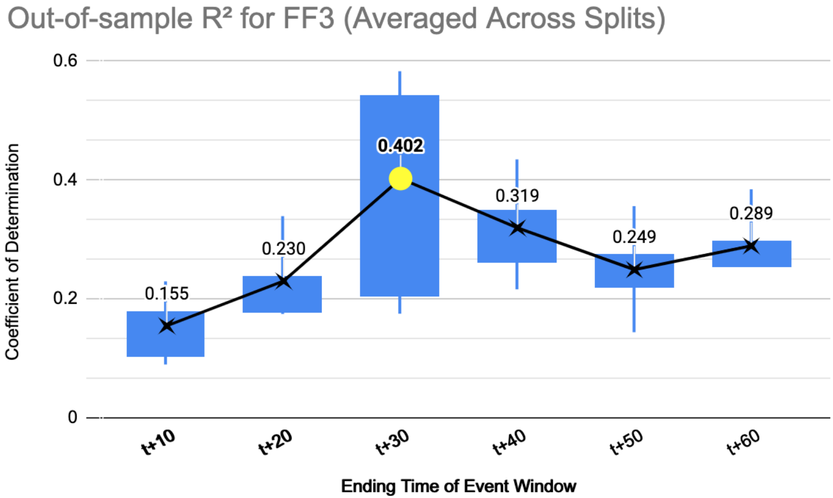
- Purpose in ML Literature: See how well model performs on unseen data whilst addressing overfitting
- Popular usage: Model selection
- **One Model**: Reduce prediction variation coming from splits themselves
  1. Allows model to predict for all sample observations
  2. Some splits might be $\uparrow$ "lucky" than others

Tuning XLNet-Base Hyperparameters

Back to Loop

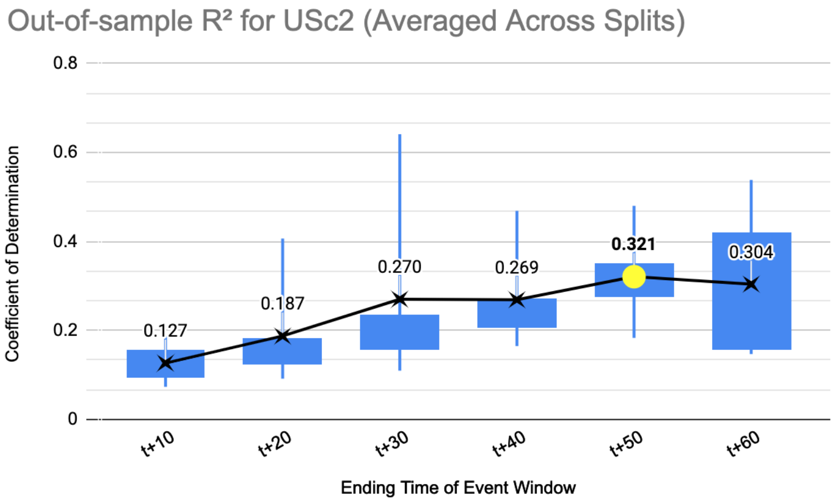
- Hyperparameters: Variables outside NN structure that affect training performance
  - "Tuned" hyperparameter: Learning rate
  - Analogy: CPU & GPU overclocking (e.g., voltage, temperature, clock frequencies)
- For each 10-minute interval, "tune" learning rate of XLNet:
  - "Best chance" of approximating f(FOMC statement text) = DP_{t+n}
  - Tuning process takes 1 computation day for each DP_{t+n}

Optimal Event Windows: *FF3*



Optimal Event Windows: *USc2*

Summary Visual Summary Text



Optimal Event Windows: R^2_{OOS} Table (1/2)

Back to Summary Text

Asset	$\overline{R^2_{OOS}}$, 30-min	$\overline{R^2_{OOS}}$, Optimal	**Difference**
$FF1$	35.0%	37.2%	**+2.2 p.p.**
$FF2$	28.7%	34.5%	**+5.8 p.p.**
$FF3$	23.0%	40.2%	**+17.2 p.p.**
$FF4$	29.8%	43.3%	**+13.5 p.p.**
$EDcm2$	18.3%	23.3%	**+5 p.p.**
$EDcm3$	14.0%	18.2%	**+4.2 p.p.**
$EDcm4$	11.2%	16.0%	**+4.8 p.p.**
$TUc1$	21.3%	24.4%	**+3.1 p.p.**
$TUc2$	16.5%	19.4%	**+2.9 p.p.**

Table 5: Differences of $\overline{R^2_{OOS}}$ between 30-minute and Optimal Event Windows (cont.)

Optimal Event Windows: R^2_{OOS} Table (2/2)

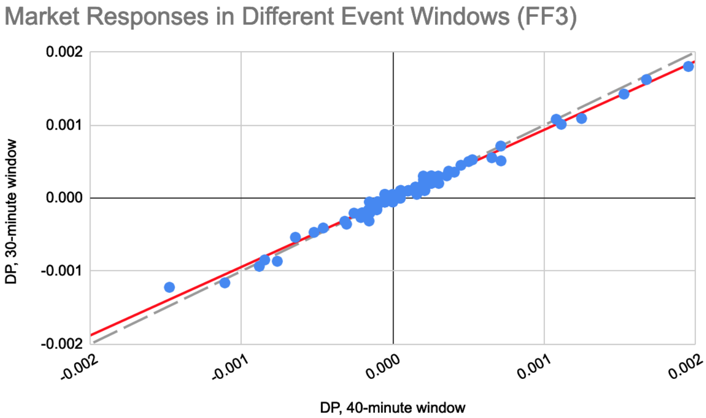
Back to Summary Text

Asset	$\overline{R^2_{OOS}}$, 30-min	$\overline{R^2_{OOS}}$, Optimal	**Difference**
$FVc1$	11.7%	21.4%	**+9.7 p.p.**
$FVc2$	12.7%	19.2%	**+6.5 p.p.**
$TYc1$	11.7%	25.5%	**+13.8 p.p.**
$TYc2$	11.4%	23.9%	**+12.5 p.p.**
$USc1$	15.7%	28.5%	**+12.8 p.p.**
$USc2$	18.7%	32.1%	**+13.4 p.p.**
SPX	18.4%	23.2%	**+4.8 p.p.**
$ESc1$	22.9%	27.7%	**+4.8 p.p.**
$ESc2$	19.3%	23.5%	**+4.2 p.p.**

Table 6: Differences of $\overline{R^2_{OOS}}$ between 30-minute and Optimal Event Windows

Optimal Event Windows: Diff Windows, Diff Responses ($FF3^{***}$)

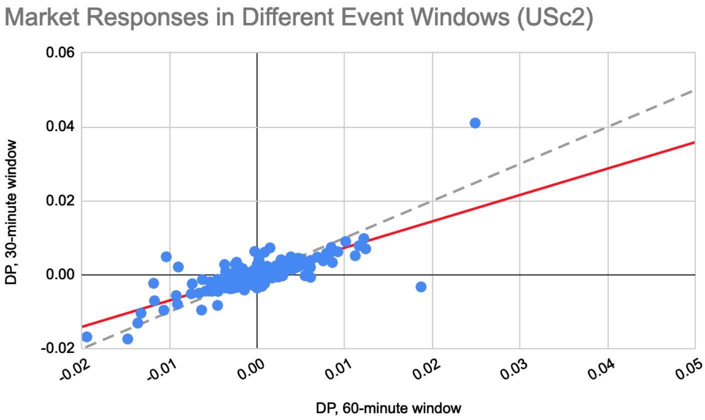
Other Assets



- **Takeaway**: On average, markets under-react, ex-post, to FOMC statement text
- "Soft" information = Longer to process → Info asymmetry to resolve
  - Indriawan et al. (2021); Brooks et al. (2023)

Optimal Event Windows: Diff Windows, Diff Responses (*USc2****)

Other Assets



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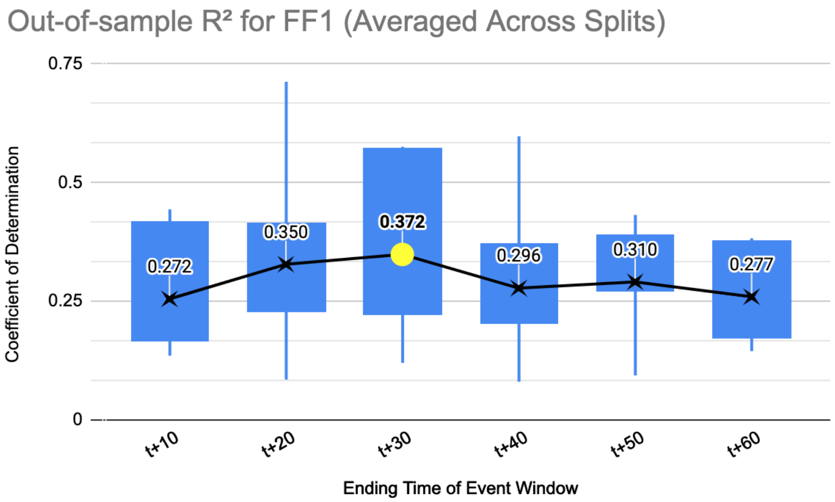
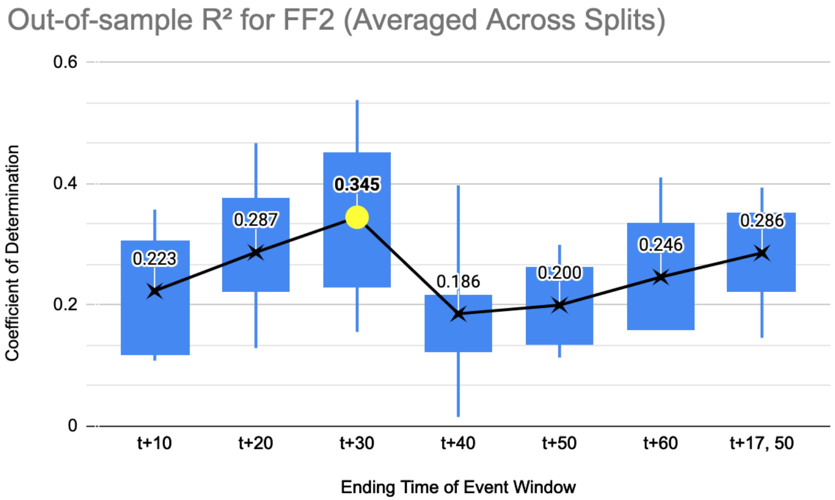
Optimal Event Windows: *FF*1

Back to Summary Text



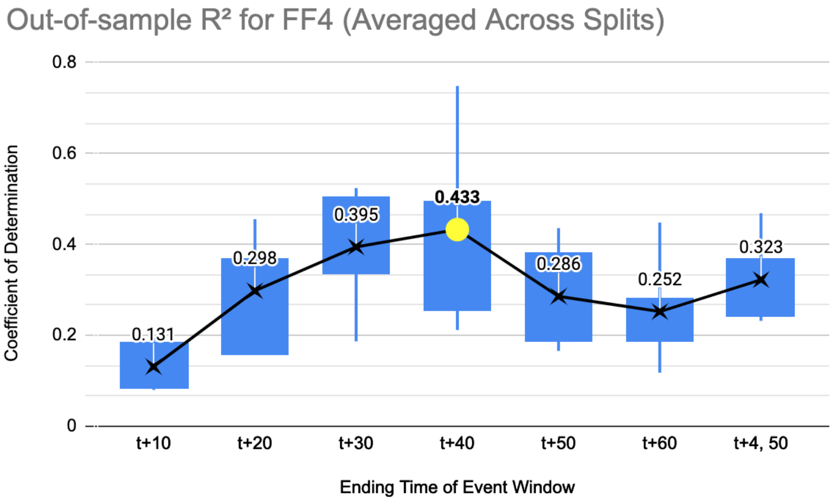
Optimal Event Windows: *FF*2

Back to Summary Text One Signal



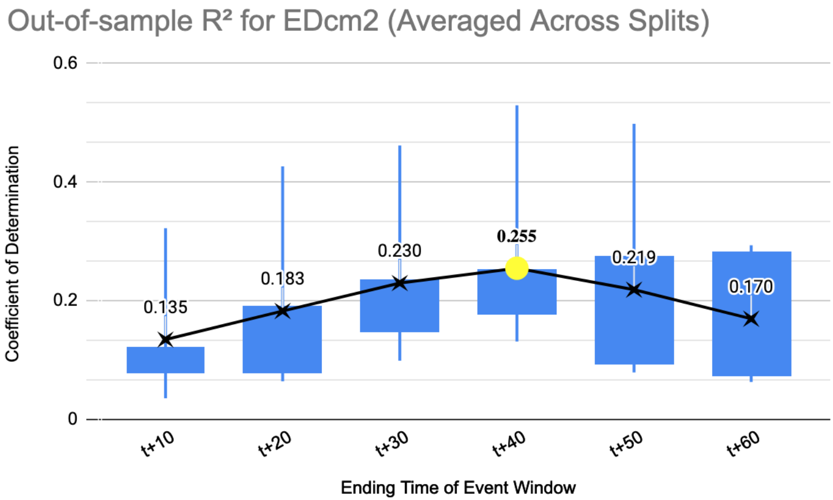
Optimal Event Windows: *FF*4

Back to Summary Text One Signal



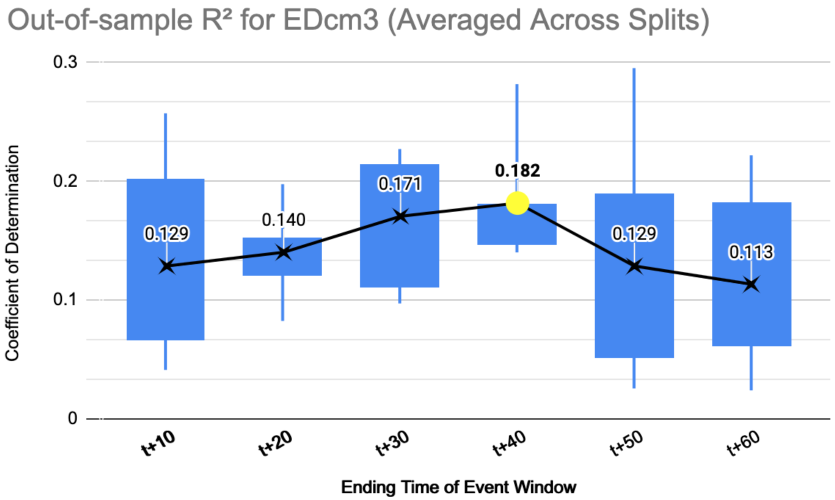
Optimal Event Windows: *EDcm2*

Back to Summary Text



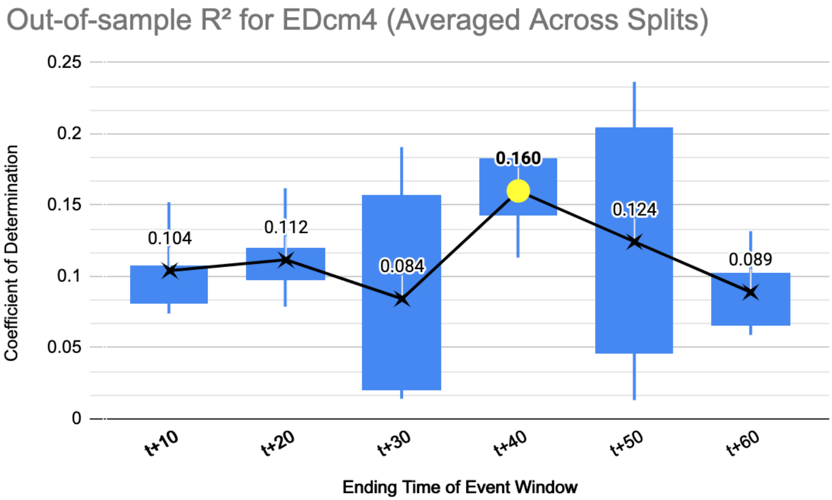
Optimal Event Windows: *EDcm3*

Back to Summary Text



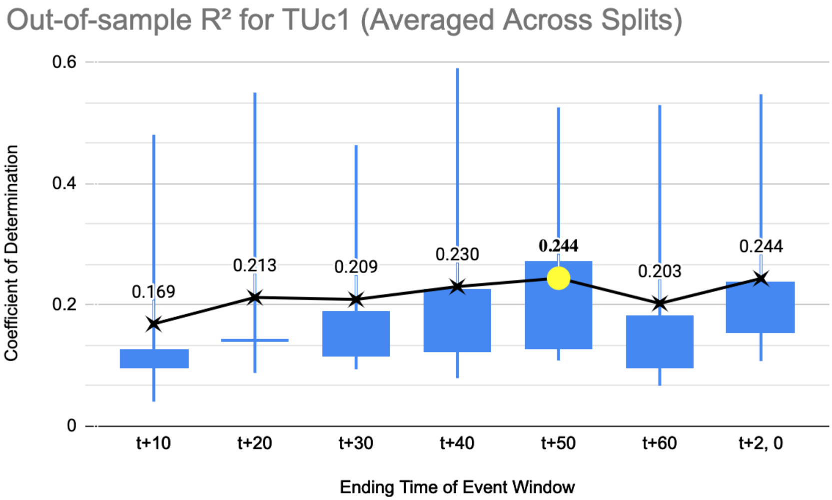
Optimal Event Windows: *EDcm4*

Back to Summary Text



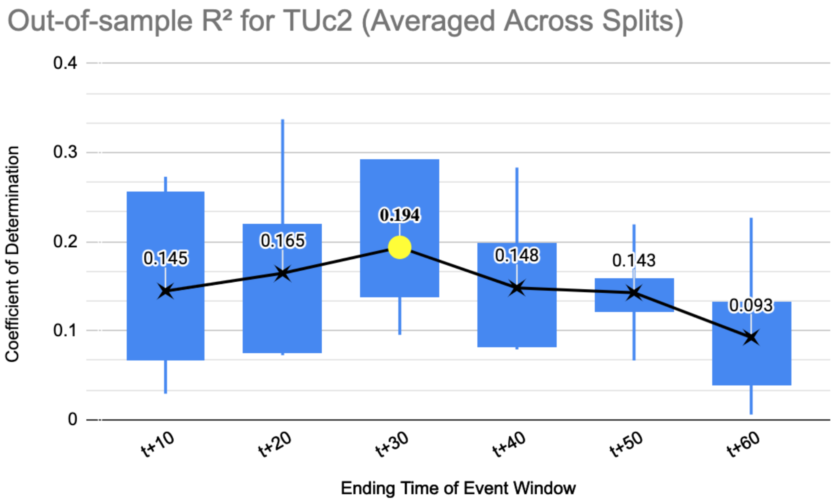
Optimal Event Windows: *TUc*1

Back to Summary Text One Signal



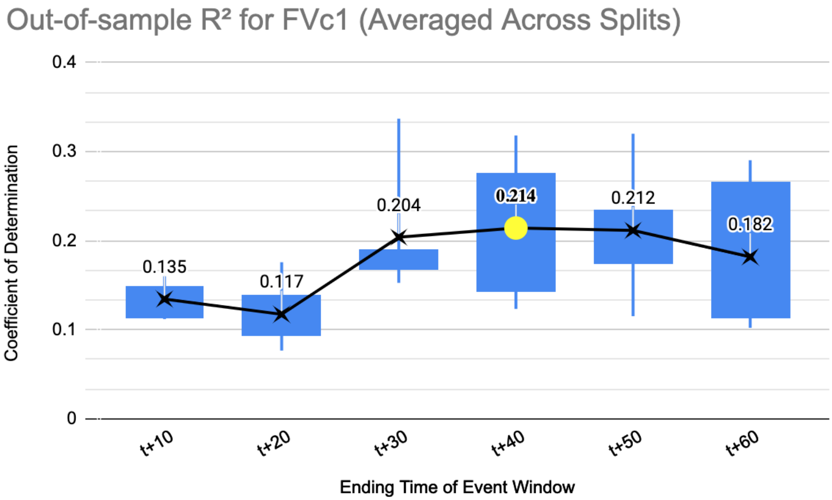
Optimal Event Windows: *TUc2*

Back to Summary Text



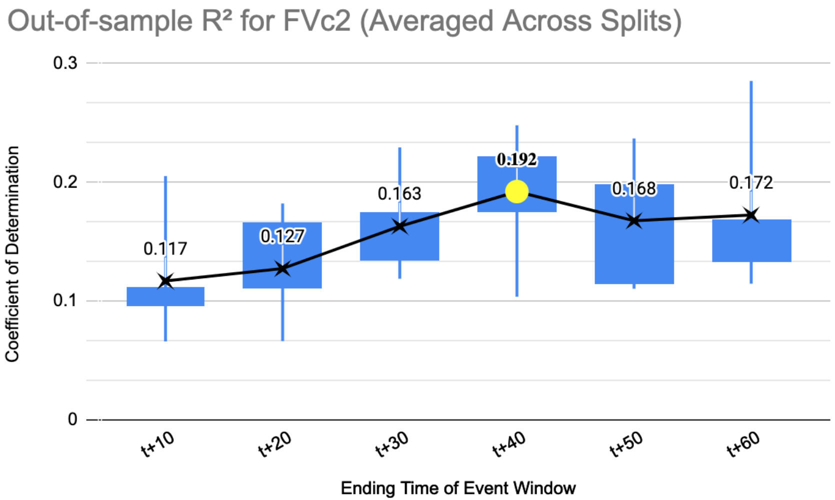
Optimal Event Windows: *FVc*1

Back to Summary Text



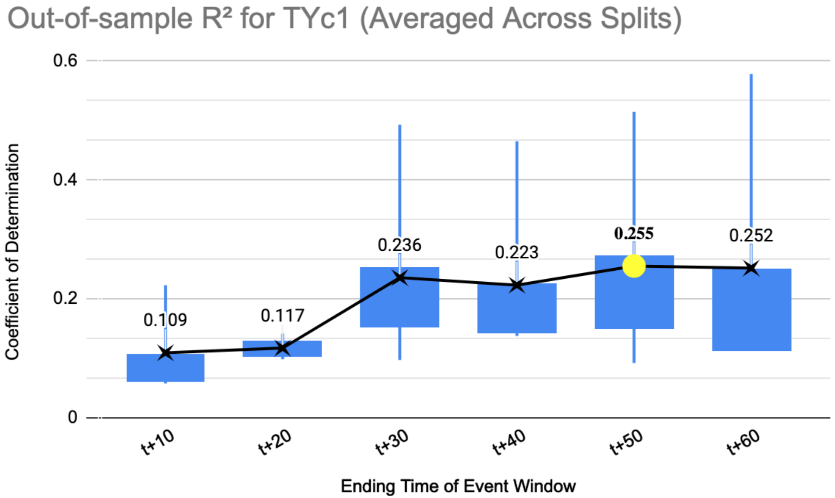
Optimal Event Windows: *FVc2*

Back to Summary Text



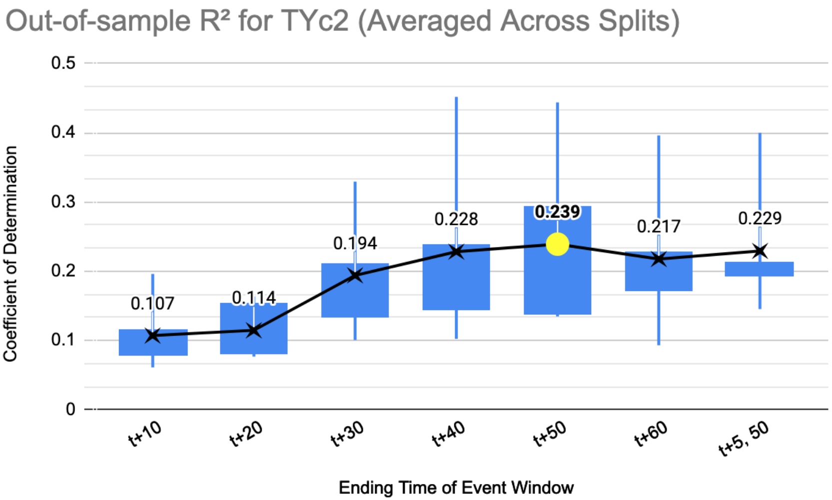
Optimal Event Windows: *TYc*1

Back to Summary Text



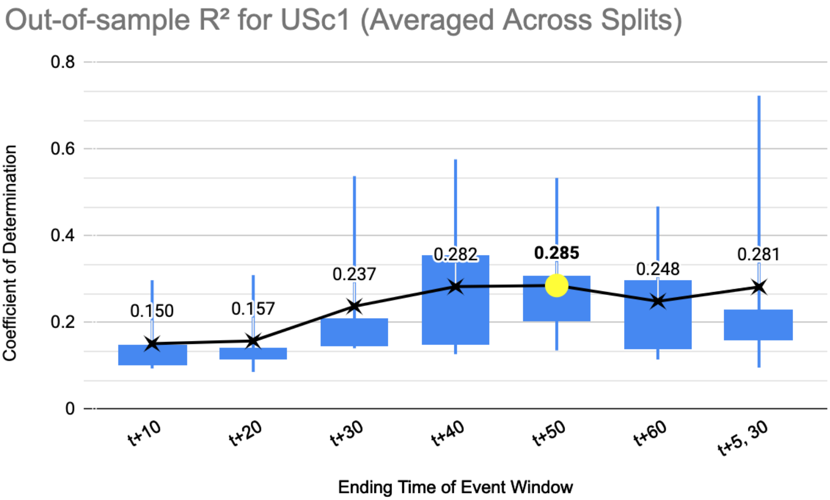
Estimating Optimal Event Windows: *TYc2*

Back to Summary Text One Signal



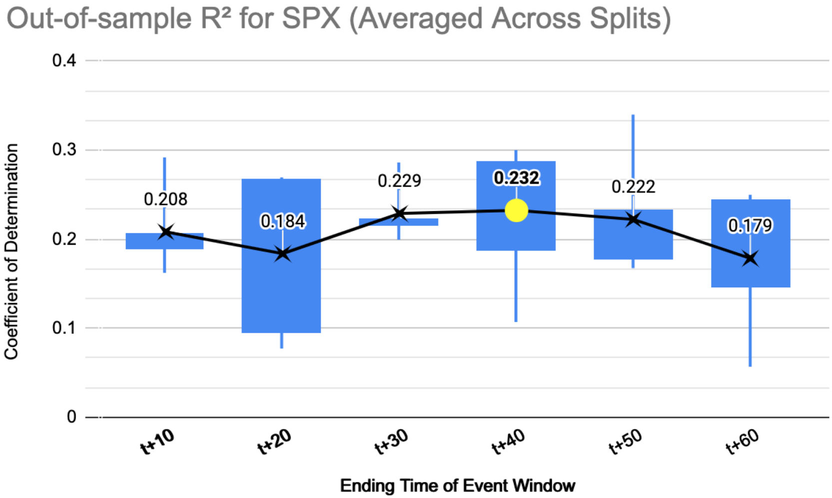
Optimal Event Windows: *USc*1

Back to Summary Text One Signal



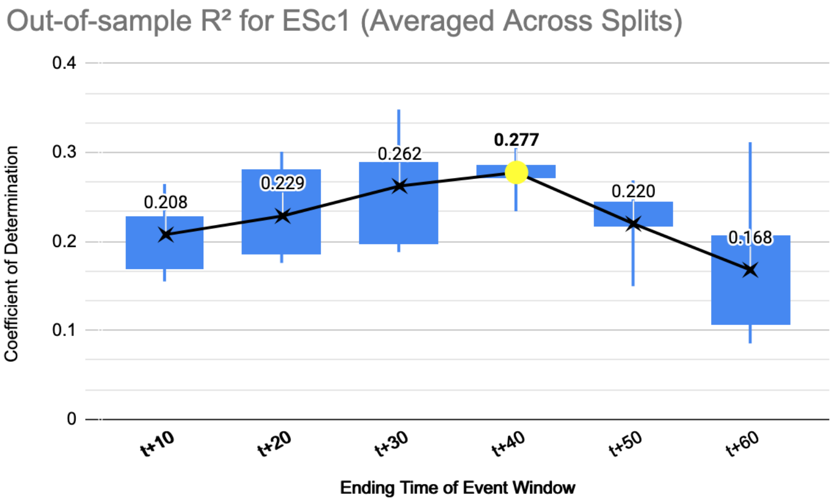
Optimal Event Windows: *SPX*

Back to Summary Text



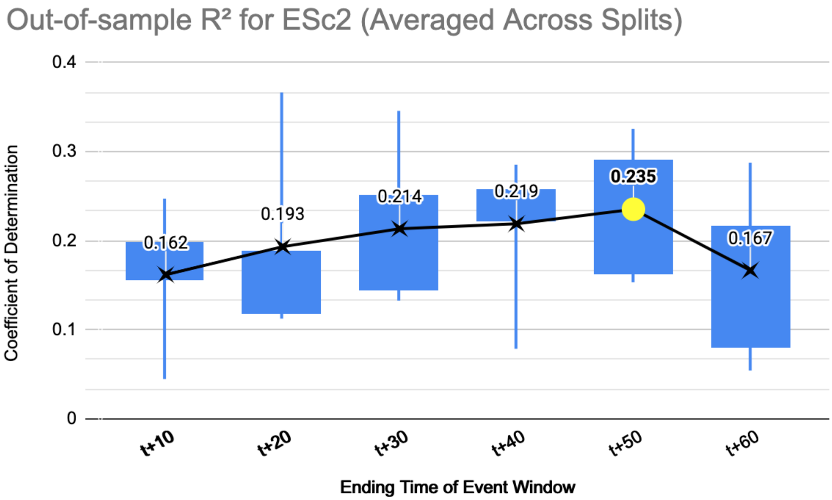
Optimal Event Windows: *ESc*1

Back to Summary Text



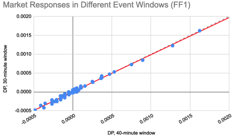
Optimal Event Windows: *ESc2*

Back to Summary Text

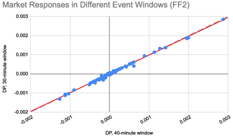


Optimal Event Windows: Diff Windows, Diff Responses (1/2)

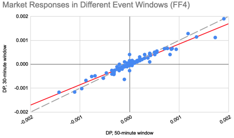
FF3 USc2



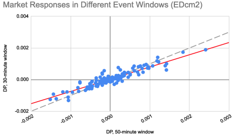
(a) *FF1***



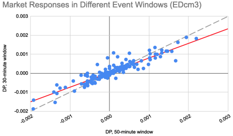
(b) *FF2****



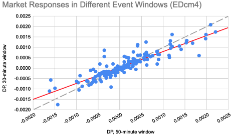
(c) *FF4****



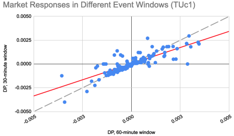
(d) *EDcm2****



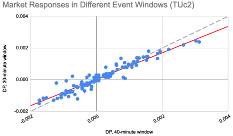
(e) *EDcm3****



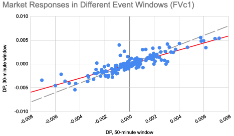
(f) *EDcm4****



(g) *TUc1****



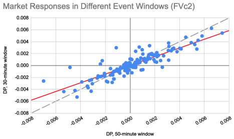
(h) *TUc2****



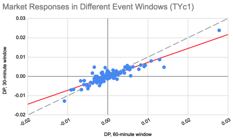
(i) *FVc1****

Optimal Event Windows: Diff Windows, Diff Responses (2/2)

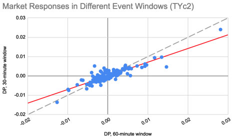
FF3 USc2



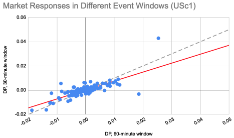
(a) $FVc2^{***}$



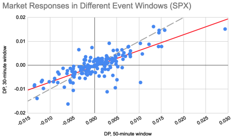
(b) $TYc1^{***}$



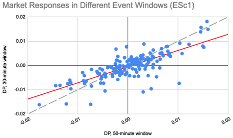
(c) $TYc2^{***}$



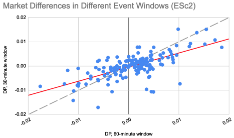
(d) $USc1^{***}$



(e) SPX^{***}



(f) $ESc1^{***}$



(g) $ESc2^{***}$

Interest-rate Futures Prices into MP Surprises: *mp*1

Back to MP surprises

- For given expiry month, FFF pays out, on last day, 100– avg FFR
- Price of $(1-j)$ month-ahead FFF at time t for FOMC meeting τ: $p^{FFj}_{\tau,t}$
- Expected avg FFR at t for τ: $FFj_{\tau,t} = 100 - p^{FFj}_{\tau,t}$

$\longrightarrow$ Current-meeting FFR surprise $mp1_{\tau,t+n}$:

$$mp1_{\tau,t+n} = \frac{m}{m-d}\left(FF1_{\tau,t+n} - FF1_{\tau,t-10}\right), \tag{9}$$

- Day d of month, days m in month
- If $m-d+1 \leq 7 \implies mp1_{\tau,t+n} = FF2_{\tau,t+n} - FF2_{\tau,t-10}$
- **Futures Contracts**: $FF1$, $FF2$

Interest-rate Futures Prices into MP Surprises: $mp2$

Back to MP surprises

- Number of months out $(j-1)$ containing next meeting
- Next-meeting FFR surprise $mp2_{\tau,t+n}$:

$$mp2_{\tau,t+n} = \frac{m_2}{m_2 - d_2}\left\{\left[FFj_{\tau,t+n} - FFj_{\tau,t-10}\right] - \frac{d2}{m2} mp1_{\tau,t+n}\right\}, \tag{10}$$

- Day d_2 of next-meeting month, days m_2 in next-meeting month
- If $m_2 - d_2 + 1 \leq 7 \implies mp2_{\tau,t+n} = FF(j+1)_{\tau,t+n} - FF(j+1)_{\tau,t-10}$
- **Futures Contracts**: $FF2, FF3, FF4$

Interest-rate Futures Prices into MP Surprises: Δedj

Back to MP surprises

- On last day of last quarter, ED pays out 100– 3-month US dollar BBA LIBOR rate
- Price at time t of j^{th} nearest quarterly ED contract for meeting τ: $p^{edj}_{\tau,t}$
- Implied rate at t for τ: $edj_{\tau,t} = 100 - p^{edj}_{\tau,t}$

$\longrightarrow$ Implied rate surprise j–quarters out $edj_{\tau,t+n}$:

$$edj_{\tau,t+n} = edj_{\tau,t+n} - edj_{\tau,t-10}, \tag{11}$$

- Day d of month, days m in month
- **Futures Contracts**: $EDcm2$, $EDcm3$, $EDcm4$

Interest-rate Futures Prices into MP Surprises: Δtk

Back to MP surprises

- On expiry quarter, Tsy futures obliges seller to deliver bond within maturities range
- Price at time t of j^{th} nearest quarterly k-year Treasury contract for meeting τ: $p^{tj^k}_{\tau,t}$

→ Implied yield surprise for meeting τ $tk_{\tau,t+n}$:

$$tk_{\tau,t+n} = -\left(p^{tk^j}_{\tau,t+n} - p^{tk^j}_{\tau,t-10}\right)/l, \tag{12}$$

- If $\tau \in \{\text{Mar, Jun, Sep, Dec}\} \implies tk_{\tau,t+n} = -\left(p^{tk^{j+1}}_{\tau,t+n} - p^{tk^{j+1}}_{\tau,t-10}\right)/l$
- Approximated maturities $l \in \{2, 4, 7, 15\}$ by Gürkaynak, Kisacikoğlu, et al. (2020)
- **Futures Contracts**: $TUc1$, $TUc2$; $FVc1$, $FVc2$; $TYc1$, $TYc2$; $USc1$, $USc2$

Principal Component Analysis

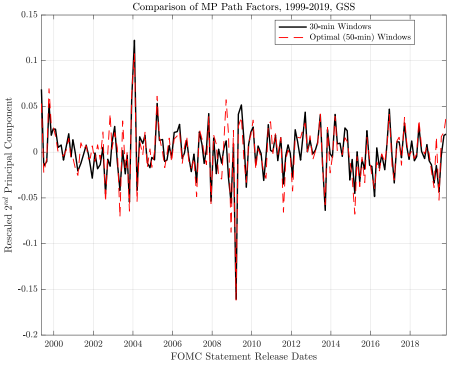
Back to MP Shocks

- **Purpose**: Reduces dimensionality without sacrificing data variation
- **Example**: Variables x^1, x^2; N observations
- 1^{st} Principal component: $\underbrace{PC1}_{N\times1} = \underbrace{X}_{N\times2} \cdot \underbrace{V}_{2\times1}$,
    1. X = Covariance matrix of variables
    2. V = Eigenvector of covariance matrix X that has largest eigenvalue
- Largest eigenvalue $\longrightarrow$ Captures most common variation in data

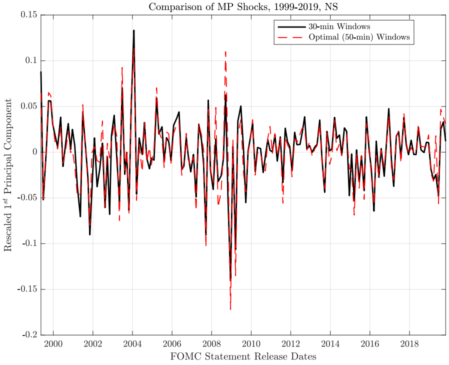
$\longrightarrow$ Corresponding eigenvector is "direction" explaining data variation

Monetary Policy Shocks: Visual Diff from Window Choice (1/2)

Back to MP Shocks



(a) GSS_P

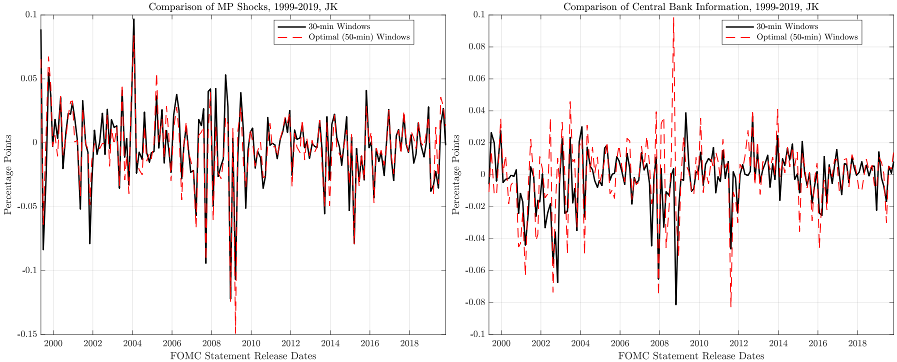


(b) NS_{MP}

Figure 1: Comparing MP Shock Series Derived from Optimal Window Length v. 30 Minutes

Monetary Policy Shocks: Visual Diff from Window Choice (2/2)

Back to MP Shocks



(a) JK_{MP} (b) JK_{CBI}

Figure 2: Comparing MP Shock Series Derived from Optimal Window Length v. 30 Minutes

Monetary Policy Shocks, Statement Frequency: Summary Table

Back to MP Shocks

Metric	GSS_T	GSS_P	NS_{MP}	JK_{MP}	JK_{CBI}
Count	165	165	165	165	165
	(165)	(165)	(165)	(165)	(165)
Mean	0	0	0	-0.0023	-0.0028
	(0)	(0)	(0)	(-0.0035)	(-0.0004)
SD	0.0219	0.0282	0.0356	0.0305	0.0180
	(0.0216)	(0.0309)	(0.0375)	(0.0297)	(0.0233)
Max	0.0756	0.1223	0.1333	0.0968	0.0388
	(0.0652)	(0.1079)	(0.1135)	(0.0840)	(0.0984)
75^{th}	0.0076	0.0134	0.0193	0.0175	0.0069
	(0.0084)	(0.0167)	(0.0203)	(0.0124)	(0.0112)
Median	0.0011	-0.0010	0.0033	-0.0017	-0.0003
	(0.0023)	(0.0019)	(0.0003)	(-0.0009)	(0.0022)
25^{th}	-0.0069	-0.0124	-0.0187	-0.0153	-0.0086
	(-0.0077)	(-0.0127)	(-0.0164)	(-0.0138)	(-0.0103)
Min	-0.1038	-0.1611	-0.1403	-0.1222	-0.0812
	(-0.1025)	(-0.1618)	(-0.1722)	(-0.1491)	(-0.0828)

Table 7: Descriptive Statistics for Monetary Policy Shock Series, FOMC Statement Frequency for 1999–2019

Impulse Response Variables: Summary Table

Back to LP

Metric	$ln(CPI)$	$ln(IP)$	EBP	TY_2
Count	246	246	246	246
Mean	5.356	4.597	0.110	2.210
SD	0.126	0.057	0.715	1.794
Max	5.551	4.706	3.283	6.650
75^{th}	5.466	4.642	0.341	3.569
Median	5.381	4.605	-0.108	1.673
25^{th}	5.241	4.548	-0.334	0.662
Min	5.112	4.467	-1.140	0.188

Table 8: Descriptive Statistics for Impulse Response Variables, Monthly for 1999–2019

Monetary Policy Shocks, Monthly Frequency: Summary Table

Back to LP

- Months without FOMC meeting → Shock values set to zero

Metric	GSS_T	GSS_P	NS_{MP}	JK_{MP}	JK_{CBI}
Count	165	165	165	165	165
	(165)	(165)	(165)	(165)	(165)
Mean	0	0	0	-0.0015	-0.0019
	(0)	(0)	(0)	(-0.0024)	(-0.0002)
SD	0.0180	0.0230	0.0291	0.0250	0.0148
	(0.0177)	(0.0253)	(0.0307)	(0.0243)	(0.0190)
Max	0.0756	0.1223	0.1333	0.0968	0.0388
	(0.0652)	(0.1079)	(0.1135)	(0.0840)	(0.0984)
75^{th}	0.0042	0.0078	0.0114	0.0055	0.0031
	(0.0042)	(0.0089)	(0.0110)	(0.0058)	(0.0075)
Median	0	0	0	0	0
	(0)	(0)	(0)	(0)	(0)
25^{th}	-0.0021	-0.0064	-0.0036	-0.0073	-0.0037
	(-0.0011)	(-0.0052)	(-0.0039)	(-0.0070)	(-0.0035)
Min	-0.1038	-0.1611	-0.1403	-0.1222	-0.0812
	(-0.1025)	(-0.1618)	(-0.1722)	(-0.1491)	(-0.0828)

Table 9: Descriptive Statistics for Monetary Policy Shock Series, Monthly Frequency for 1999–2019

MP Shocks: Nominal Interest Rates

Back to Reg Results

	30-minute Window				Optimal Window				**Difference**		
	ΔTY_1	ΔTY_2	ΔTY_5	ΔTY_{10}	ΔTY_1	ΔTY_2	ΔTY_5	ΔTY_{10}	ΔTY_2	ΔTY_5	ΔTY_{10}
GSS_T	1.00***	0.82***	0.15	-0.37	1.00***	0.78***	0.08	-0.42	**-0.04**	**-0.07**	**-0.05**
	(0.28)	(0.34)	(0.43)	(0.41)	(0.23)	(0.28)	(0.33)	(0.32)			
GSS_P	1.00***	1.46***	1.89***	1.64***	1.00***	1.51***	1.93***	1.66***	**+0.05**	**+0.04**	**+0.02**
	(0.09)	(0.09)	(0.25)	(0.36)	(0.11)	(0.10)	(0.21)	(0.30)			
NS_{MP}	1.00***	1.24***	1.29***	0.95***	1.00***	1.30***	1.39***	1.06***	**+0.06**	**+0.11**	**+0.11**
	(0.07)	(0.09)	(0.19)	(0.25)	(0.09)	(0.10)	(0.18)	(0.24)			
JK_{MP}	1.00***	1.30***	1.39***	0.99***	1.00***	1.35***	1.52***	1.16***	**+0.04**	**+0.13**	**+0.17**
	(0.11)	(0.15)	(0.28)	(0.36)	(0.12)	(0.16)	(0.32)	(0.43)			
JK_{CBI}	1.00***	1.04***	1.00***	0.82***	1.00***	1.20***	1.14***	0.85***	**+0.16**	**+0.14**	**+0.03**
	(0.25)	(0.30)	(0.31)	(0.29)	(0.23)	(0.25)	(0.27)	(0.26)			

Table 10: Diff in Responses of Nominal Interest Rates to Shocks from Event Window Choice

$\longrightarrow$ Using optimal windows $\longrightarrow$ Bigger effects for MP shocks about forward guidance

MP Shocks: Real Interest Rates

Back to Reg Results

	30-minute Window			Optimal Window			**Difference**		
	$\Delta TIPS_2$	$\Delta TIPS_5$	$\Delta TIPS_{10}$	$\Delta TIPS_2$	$\Delta TIPS_5$	$\Delta TIPS_{10}$	$\Delta TIPS_2$	$\Delta TIPS_5$	$\Delta TIPS_{10}$
GSS_T	-0.81	0.02	-0.19	-0.90	0.09	-0.16	**-0.09**	**+0.07**	**+0.03**
	(1.44)	(0.51)	(0.45)	(1.57)	(0.46)	(0.37)			
GSS_P	2.21***	1.96***	1.74***	2.20***	2.03***	1.75***	**-0.00**	**+0.06**	**+0.01**
	(0.49)	(0.46)	(0.44)	(0.37)	(0.38)	(0.37)			
NS_{MP}	1.17***	1.29***	1.08***	1.31***	1.47***	1.20***	**+0.14**	**+0.18**	**+0.13**
	(0.73)	(0.36)	(0.30)	(0.63)	(0.31)	(0.28)			
JK_{MP}	1.40***	1.40***	1.15***	1.66***	1.64***	1.38***	**+0.26**	**+0.24**	**+0.23**
	(0.83)	(0.47)	(0.41)	(0.63)	(0.49)	(0.46)			
JK_{CBI}	0.51	0.99***	0.85***	0.60	1.13***	0.84***	**+0.09**	**+0.14**	**-0.01**
	(0.85)	(0.33)	(0.25)	(0.92)	(0.33)	(0.25)			

Table 11: Diff in Responses of Real Interest Rates to Shocks from Event Window Choice

→ Using optimal windows → Bigger effects for MP shocks about forward guidance

MP Shocks: Break-even Inflation

Back to Reg Results

	30-minute Window			Optimal Window			**Difference**		
	ΔBEI_2	ΔBEI_5	ΔBEI_{10}	ΔBEI_2	ΔBEI_5	ΔBEI_{10}	ΔBEI_2	ΔBEI_5	ΔBEI_{10}
GSS_T	1.63***	0.13	-0.18	1.67***	-0.01	−0.26**	**+0.05**	**-0.14**	**-0.08**
	(1.46)	(0.29)	(0.17)	(1.58)	(0.29)	(0.17)			
GSS_P	-0.75	-0.08	-0.10	−0.69*	-0.10	-0.09	**+0.06**	**-0.02**	**+0.01**
	(0.46)	(0.24)	(0.12)	(0.36)	(0.23)	(0.12)			
NS_{MP}	0.07	-0.01	−0.13*	-0.01	-0.07	−0.14**	**-0.08**	**-0.07**	**-0.01**
	(0.70)	(0.23)	(0.12)	(0.65)	(0.23)	(0.12)			
JK_{MP}	-0.09	-0.01	−0.17**	-0.31	-0.12	−0.22***	**-0.22**	**-0.11**	**-0.05**
	(0.81)	(0.29)	(0.13)	(0.61)	(0.25)	(0.11)			
JK_{CBI}	0.54	0.01	-0.02	0.60	0.01	0.02	**+0.07**	**+0.00**	**+0.04**
	(0.76)	(0.29)	(0.20)	(0.86)	(0.30)	(0.23)			

Table 12: Diff in Responses of Break-even Inflation to Shocks from Event Window Choice

→ Using optimal windows → Bigger effects for MP shocks about forward guidance

MP Shocks: Stock Prices

Back to Reg Results

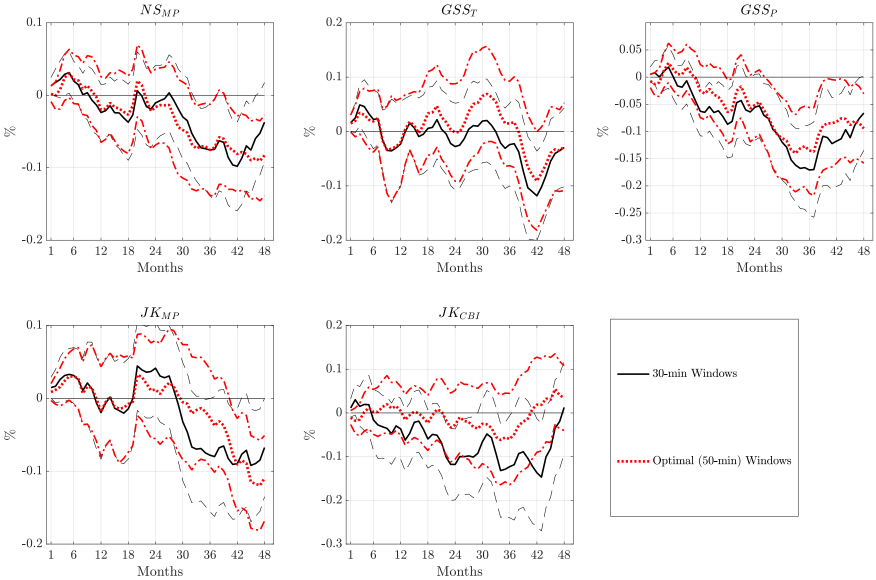
	30-minute Window			Optimal Window			**Percentage Difference**		
	DP_{SPX}	DP_{ESc1}	DP_{ESc2}	DP_{SPX}	DP_{ESc1}	DP_{ESc2}	DP_{SPX}	DP_{ESc1}	DP_{ESc2}
GSS_T	-8.40^{***}	-8.83^{***}	-7.25^{***}	-7.39^{***}	-7.43^{***}	-7.34^{***}	**-11.99%**	**-15.92%**	**+1.25%**
	(2.71)	(2.68)	(2.78)	(3.10)	(3.15)	(3.12)			
GSS_P	-6.14^{***}	-6.27^{***}	-6.12^{***}	-6.85^{***}	-6.96^{***}	-7.63^{***}	**+11.51%**	**+11.00%**	**+24.61%**
	(1.81)	(1.83)	(1.76)	(2.88)	(2.91)	(2.81)			
NS_{MP}	-6.92^{***}	-7.15^{***}	-6.51^{***}	-7.00^{***}	-7.10^{***}	-7.55^{***}	**+1.23%**	**-1.00%**	**+16.00%**
	(1.32)	(1.37)	(1.31)	(1.85)	(1.89)	(1.84)			
JK_{MP}	-14.76^{***}	-15.08^{***}	-13.73^{***}	-17.46^{***}	-17.77^{***}	-17.30^{***}	**+18.25%**	**+17.88%**	**+26.00%**
	(0.81)	(0.91)	(0.94)	(1.04)	(1.08)	(1.06)			
JK_{CBI}	15.19^{***}	13.84^{***}	15.18^{***}	14.08^{***}	14.44^{***}	12.12^{***}	**-7.36%**	**-4.90%**	**-12.43%**
	(2.29)	(2.35)	(2.39)	(2.11)	(2.14)	(2.07)			

Table 13: Diff in Responses of Stock Prices to Shocks from Event Window Choice
Notes: Positive (negative) values → stronger (weaker) effect in same direction

→ Using optimal windows → Bigger effects for MP shocks about forward guidance

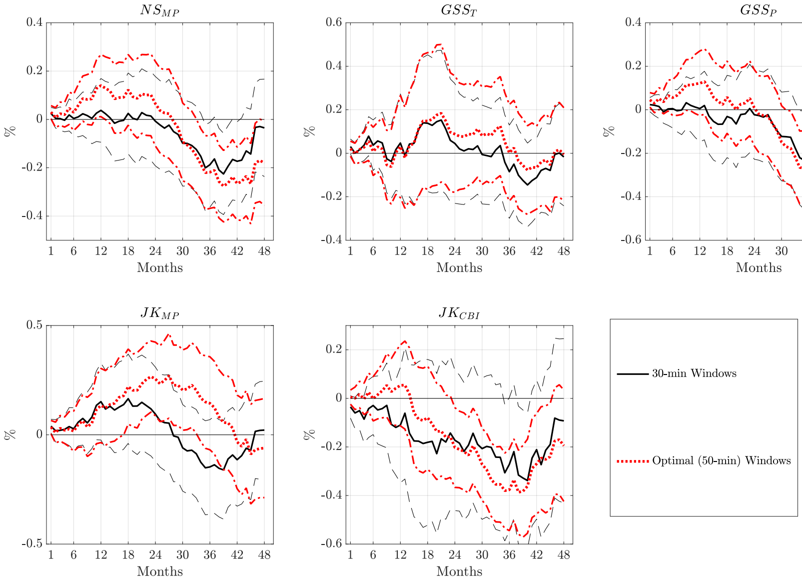
MP Shocks: Impulse Responses for CPI

Back to LP Results



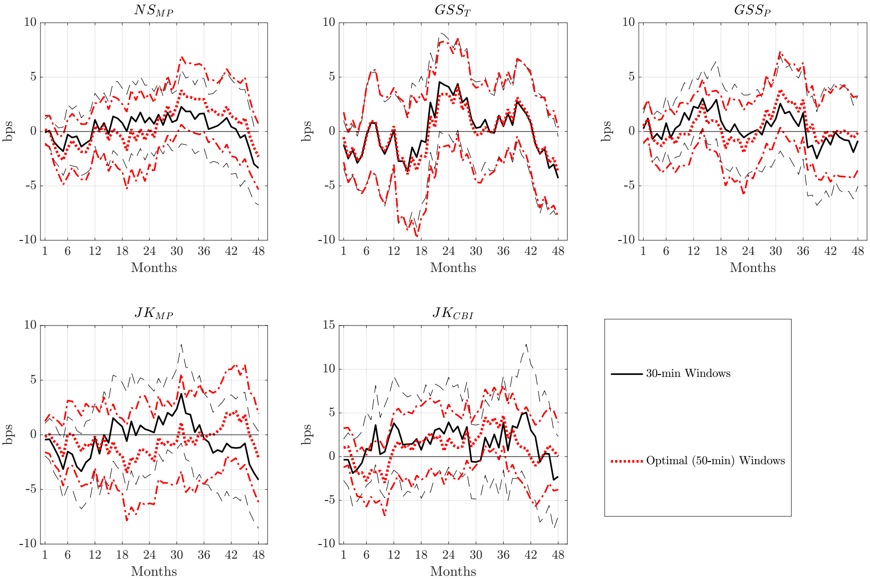
MP Shocks: Impulse Responses for IP

Back to LP Results



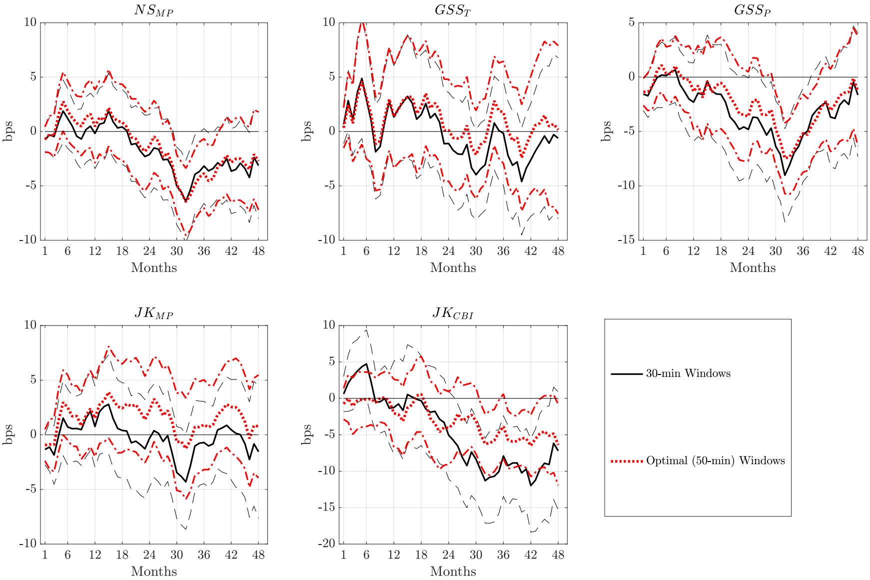
MP Shocks: Impulse Responses for EBP

Back to LP Results



MP Shocks: Impulse Responses for 2Y Treasury Yield

Back to LP Results



"Joint" and "One Signal" Approaches

Back to Main

- **Recap**: XLNet-Base approx $f(\text{FOMC Statement Text}) = DP_{t+5}, \forall \text{Folds of } \forall DP_{t+n}$

  → "Joint" estimation of signal and optimal event window length

"Joint" and "One Signal" Approaches

Back to Main

- **Recap**: XLNet-Base approx $f(\text{FOMC Statement Text}) = DP_{t+5}, \forall \text{Folds of } \forall DP_{t+n}$
  - $\longrightarrow$ "Joint" estimation of signal and optimal event window length

"Joint" and "One Signal" Approaches

Back to Main

- **Recap**: XLNet-Base approx $f(\text{FOMC Statement Text}) = DP_{t+5}, \forall \text{Folds of } \forall DP_{t+n}$
  - $\rightarrow$ "Joint" estimation of signal and optimal event window length
- Fine-tuning XLNet-Base for "joint" estimation = Computationally intensive
  - GPU + Financial constraints = Estimate optimal window lengths only up to $\mathbf{t+60}$
  - Current computation time: 249+ days

"Joint" and "One Signal" Approaches

Back to Main

- **Recap**: XLNet-Base approx f(FOMC Statement Text) = DP_{t+5}, $\forall$Folds of $\forall DP_{t+n}$
  - $\rightarrow$ "Joint" estimation of signal and optimal event window length
- Fine-tuning XLNet-Base for "joint" estimation = Computationally intensive
  - GPU + Financial constraints = Estimate optimal window lengths only up to $\mathbf{t+60}$
  - Current computation time: 249+ days
- **Assumption**: NN Predictions in "joint-estimated" event window = Constant $\forall t$[§]
  1. Much less computationally intensive
  2. Can check if FOMC statement characteristics affect optimal window length
  3. Can check if $\exists$ greater out-of-sample R^2_{OOS} for $t+n > t+60$

Robustness Check

[§] Signal from XLNet-Base is likely to change $\because$ Changing LHS DP_{t+n} $\rightarrow$ retraining NN + "Joint" estimation was performed on "general" sample of FOMC statements, not specific types of statements.

Effects of FOMC Statement Characteristics on Event Windows

Back to Main

- Use "one signal" approach to compare MSEs computed based on:
  1. Complexity of FOMC statements Complexity
  2. Similarity of FOMC statements Similarity
  3. Presence of Dissents Dissents

FOMC Statement Characteristics: Text Complexity (1/3)

Back to Characteristics

- Condition FOMC statements based on semantic complexity
  - Hernandez-Murillo and Shell (2014); Hansen and McMahon (2016); Smales and Apergis (2017); Haldane and McMahon (2018); De Pooter (2021); McMahon (2023); and others...

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- Measured based on Flesch Kincaid Grade Level Summary Stats
  - Based on sentence structure, word structure, and word phonology

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- Measured based on Flesch Kincaid Grade Level Summary Stats
  - Based on sentence structure, word structure, and word phonology
  - Range of reading Levels: 12.2–21.3
  - Median Reading Level: 16.5

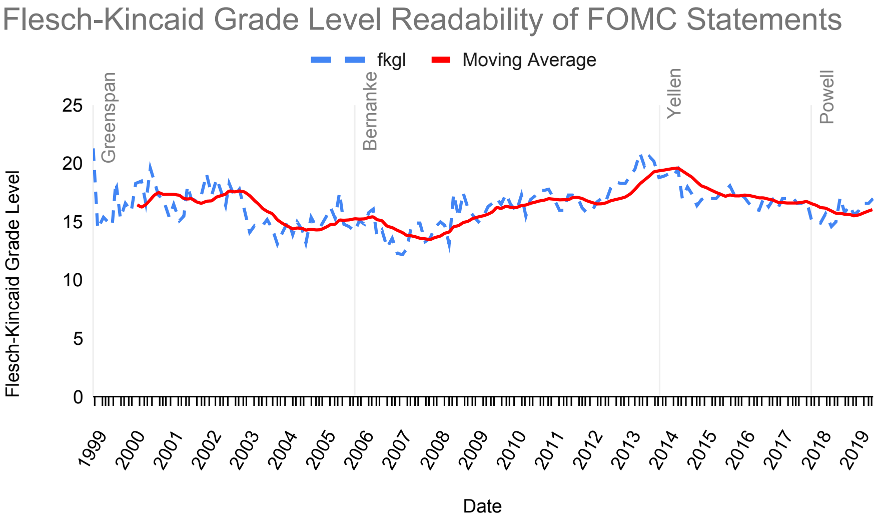
FOMC Statement Characteristics: Text Complexity (1/3)

Back to Characteristics

- Condition FOMC statements based on semantic complexity
  - Hernandez-Murillo and Shell (2014); Hansen and McMahon (2016); Smales and Apergis (2017); Haldane and McMahon (2018); De Pooter (2021); McMahon (2023); and others...
- Measured based on Flesch Kincaid Grade Level Summary Stats
  - Based on sentence structure, word structure, and word phonology
  - Range of reading Levels: 12.2–21.3
  - Median Reading Level: 16.5
- Split sample conditioned on being <= or > 16.5
- Calculate sub-set MSEs and event window lengths

FOMC Statement Characteristics: Text Complexity (2/3)

Back to Characteristics



FOMC Statement Characteristics: Text Complexity (3/3)

Back to Characteristics

Metric	Simple	**Complicated**
Minimised MSE		
Average	1.25e-5	**1.06e-5**
Event Window Length (Minutes)		
Average	60	**71**

Table 14: Average MSEs and Event Window Lengths Using the "One Signal" Approach, Conditioned by FOMC Statement Complexity

$\rightarrow$ FOMC statements with $\uparrow$ complexity $\rightarrow$ Longer event window on average

FOMC Statement Characteristics: Text Similarity (1/4)

Back to Characteristics

- Condition FOMC statements based on text similarity
  - Acosta and Meade (2015); Handlan (2022a); and others...

FOMC Statement Characteristics: Text Similarity (1/4)

Back to Characteristics

- Condition FOMC statements based on text similarity
  - Acosta and Meade (2015); Handlan (2022a); and others...
- Measured based on Term Frequency-Inverse Document Frequency (TFIDF)
  - Weighted frequency assigned to terms based on: TFIDF Equation
    1. Number of times term appears in a document
    2. Number of documents terms appears in

FOMC Statement Characteristics: Text Similarity (1/4)

Back to Characteristics

- Condition FOMC statements based on text similarity
  - Acosta and Meade (2015); Handlan (2022a); and others...
- Measured based on Term Frequency-Inverse Document Frequency (TFIDF)
  - Weighted frequency assigned to terms based on: TFIDF Equation
    1. Number of times term appears in a document
    2. Number of documents terms appears in
- Terms with ↑ $TFIDF_{d,t}$ = Informative terms at distinguishing documents d

TFIDF Terms

FOMC Statement Characteristics: Text Similarity (2/4)

Back to Characteristics

- TFIDF matrix dimensions: D documents $\times$ T terms

FOMC Statement Characteristics: Text Similarity (2/4)

Back to Characteristics

- TFIDF matrix dimensions: D documents $\times$ T terms
- Row vector: All terms t of document d represented by $TFIDF_{d,t}$ values

FOMC Statement Characteristics: Text Similarity (2/4)

Back to Characteristics

- TFIDF matrix dimensions: D documents $\times$ T terms
- Row vector: All terms t of document d represented by $TFIDF_{d,t}$ values
- All row vectors normalised by number of d and t in matrix

FOMC Statement Characteristics: Text Similarity (2/4)

Back to Characteristics

- TFIDF matrix dimensions: D documents $\times$ T terms
- Row vector: All terms t of document d represented by $TFIDF_{d,t}$ values
- All row vectors normalised by number of d and t in matrix
- $\implies$ $TFIDF \cdot TFIDF^T$ = Dot product between every pair of FOMC statements

FOMC Statement Characteristics: Text Similarity (2/4)

Back to Characteristics

- TFIDF matrix dimensions: D documents $\times$ T terms
- Row vector: All terms t of document d represented by $TFIDF_{d,t}$ values
- All row vectors normalised by number of d and t in matrix
- $\implies$ $TFIDF \cdot TFIDF^T$ = Dot product between every pair of FOMC statements
- $\implies$ Degree of similarity between 2 FOMC statements = Cosine similarity:

Similarity Matrix

$$S^{A,B} := \cos\theta = \frac{\mathbf{A} \cdot \mathbf{B}}{||\mathbf{A}||||\mathbf{B}||},$$

- **Scale**: Entirely different $= 0 \leq$ Cosine Similarity $\leq 1 =$ Exact same

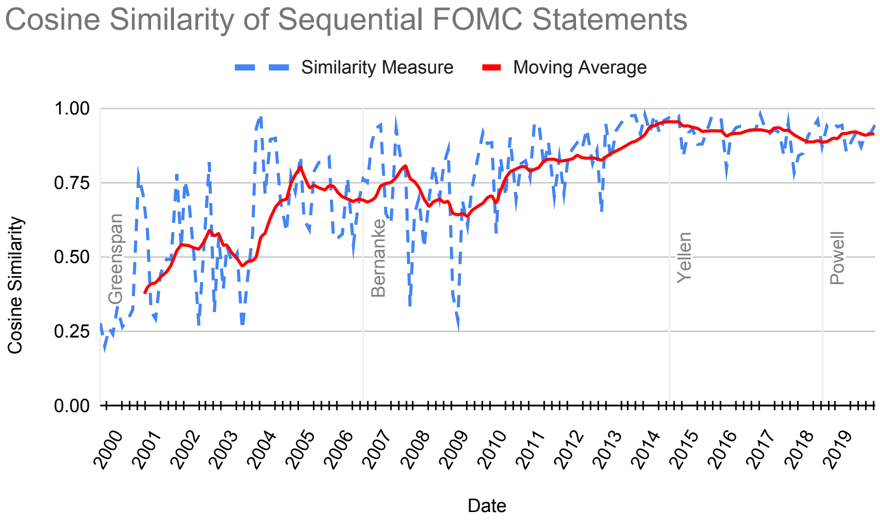
FOMC Statement Characteristic: Text Similarity (3/4)

Back to Characteristics

- $S^1 := (d, d-1)$: Degree of similarity between sequential FOMC statements
  Summary Stats
  - Range of S^1: 0.02–0.984
  - Median of S^1: 0.826
- Split sample conditioned on being $\leq$ or $>$ 0.826
- Calculate sub-set MSEs and event window lengths

FOMC Statement Characteristic: Text Similarity (3/4)

Back to Characteristics



FOMC Statement Characteristics: Text Similarity (4/4)

Back to Characteristics

Metric	**Different**	Similar
Minimised MSE		
Average	**1.18e-5**	1.13e-5
Event Window Length (Minutes)		
Average	**62**	51

Table 15: Average MSEs and Event Window Lengths Using the “One Signal” Approach, Conditioned by FOMC Statement Similarity

→ Less similar FOMC statements → Longer event windows on average

FOMC Statement Characteristics: Presence of Dissents (1/2)

Back to Characteristics

- Condition FOMC statements based presence of dissent votes or not[¶]
  - Riboni and Ruge-Murcia (2014); Tsang and Yang (2024); Bobrov et al. (2025); and others...

[¶] I do not record and distinguish between dissent votes for tighter policy, easier, policy, or other reasons.

FOMC Statement Characteristics: Presence of Dissents (1/2)

Back to Characteristics

- Condition FOMC statements based presence of dissent votes or not[¶]
  - Riboni and Ruge-Murcia (2014); Tsang and Yang (2024); Bobrov et al. (2025); and others...
- Roughly 40% of FOMC statement sample has recorded dissents
- By Fed tradition, dissents usually recorded if majority opinion = unacceptable
- Presence of dissents provides additional info. for markets to process

[¶] I do not record and distinguish between dissent votes for tighter policy, easier, policy, or other reasons.

FOMC Statement Characteristics: Presence of Dissents (1/2)

Back to Characteristics

- Condition FOMC statements based presence of dissent votes or not[¶]
  - Riboni and Ruge-Murcia (2014); Tsang and Yang (2024); Bobrov et al. (2025); and others...
- Roughly 40% of FOMC statement sample has recorded dissents
- By Fed tradition, dissents usually recorded if majority opinion = unacceptable
- Presence of dissents provides additional info. for markets to process
- Calculate sub-set MSEs and event window lengths

[¶] I do not record and distinguish between dissent votes for tighter policy, easier, policy, or other reasons.

FOMC Statement Characteristics: Presence of Dissents (2/2)

Back to Characteristics

Metric	Unity	**Dissents**
Minimised MSE		
Average	9.57e-6	**1.43e-5**
Event Window Length (Minutes)		
Average	53	**83**

Table 16: Average MSEs and Event Window Lengths Using the "One Signal" Approach, Conditioned by Presence of Dissents in FOMC Statements

$\longrightarrow$ FOMC statements with dissents $\rightarrow$ longer event windows on average

FOMC Statement Characteristics: Summary Table

Complexity S1 Similarity

Metric	FKGL	S^1
Count	165	164
Mean	16.361	0.751
SD	1.715	0.212
Max	21.3	0.984
75^{th}	17.3	0.920
Median	16.5	0.826
25^{th}	15.1	0.622
Min	12.2	0.200

Table 17: Descriptive Statistics for Heterogeneity Analyses

Robustness Check of Optimal Event Windows

Back to One Signal

1. Pick an interest-rate or equity futures contract

‖Performed for $FF2$, $FF4$, $TUc1$, $TYc2$, $USc1$.

Robustness Check of Optimal Event Windows

Back to One Signal

1. Pick an interest-rate or equity futures contract
2. Take predictions $\widehat{DP_{t+n}}$ for each $k = 5$ fold from optimal event window

[‖] Performed for $FF2$, $FF4$, $TUc1$, $TYc2$, $USc1$.

Robustness Check of Optimal Event Windows

Back to One Signal

1. Pick an interest-rate or equity futures contract
2. Take predictions $\widehat{DP_{t+n}}$ for each $k = 5$ fold from optimal event window
3. Check if $\overline{R^2_{OOS}} \forall t+n \geq \overline{R^2_{OOS}}$ in optimal window length
    - Yes: Perform "joint" estimation in that window length[‖]
    - No: Go back to step 1

[‖] Performed for $FF2$, $FF4$, $TUc1$, $TYc2$, $USc1$.

Robustness Check of Optimal Event Windows

Back to One Signal

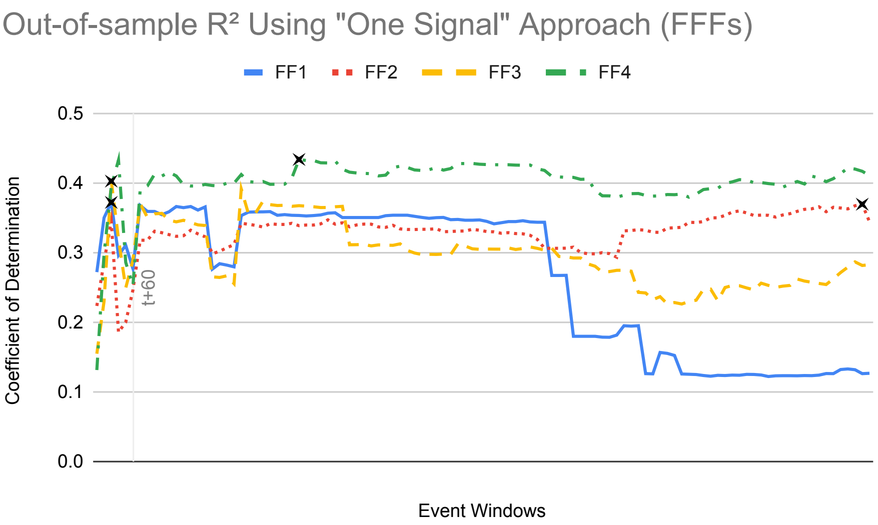
1. Pick an interest-rate or equity futures contract
2. Take predictions $\widehat{DP_{t+n}}$ for each $k = 5$ fold from optimal event window
3. Check if $\overline{R^2_{OOS}} \forall t+n \geq \overline{R^2_{OOS}}$ in optimal window length
   - Yes: Perform "joint" estimation in that window length‖
   - No: Go back to step 1

- **Results**:
  1. Optimal window length has highest $\overline{R^2_{OOS}}$
  2. "Jointly" estimated $\overline{R^2_{OOS}}$ for window $> t+60$ greater than "" for window $t+20$

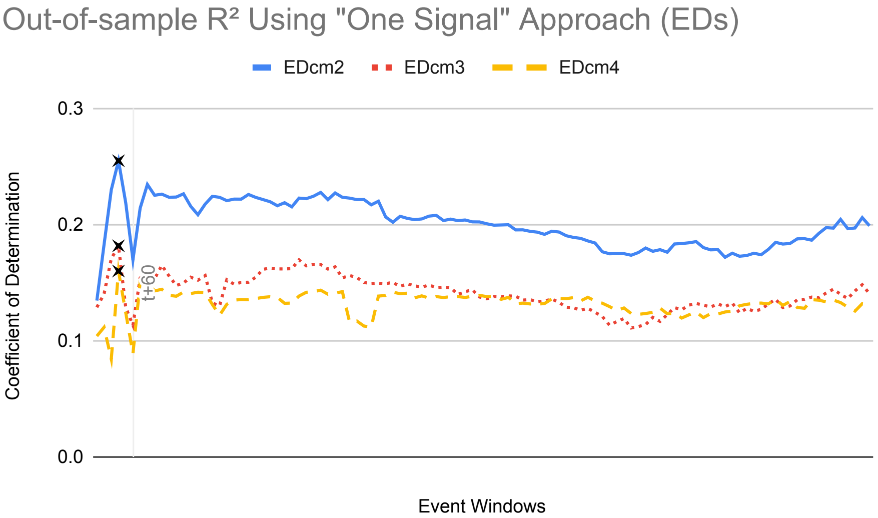
  $\longrightarrow$ Event window with global maximum $\overline{R^2_{OOS}}$ could be in window length $> t+60$

‖Performed for $FF2$, $FF4$, $TUc1$, $TYc2$, $USc1$.

Testing R^2 Using "One Signal" Approach for Federal Funds Futures FF2 FF4

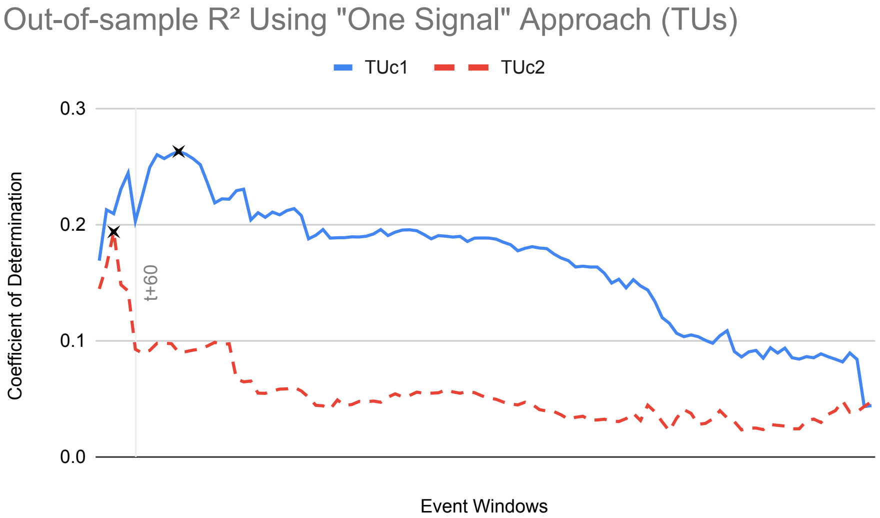


Testing R^2 Using "One Signal" Approach for Eurodollar Futures

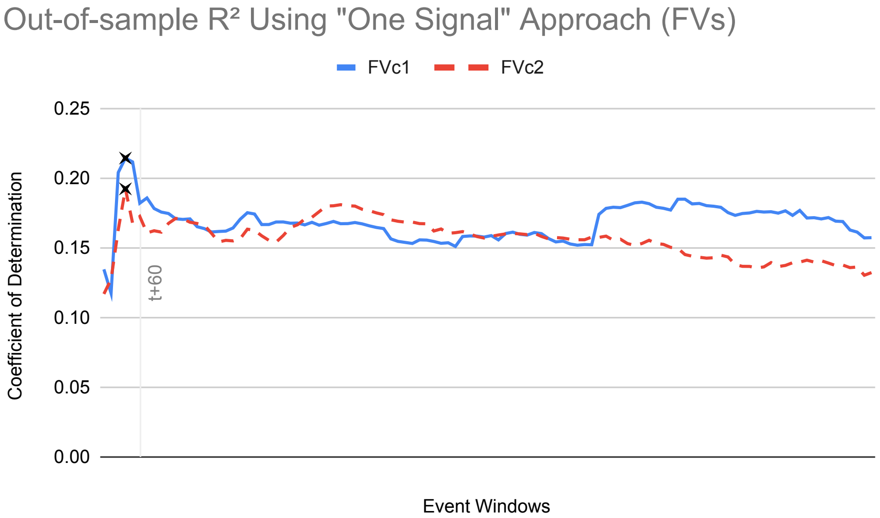


Testing R^2 Using "One Signal" Approach for 2-Year Treasury Futures

TUc1

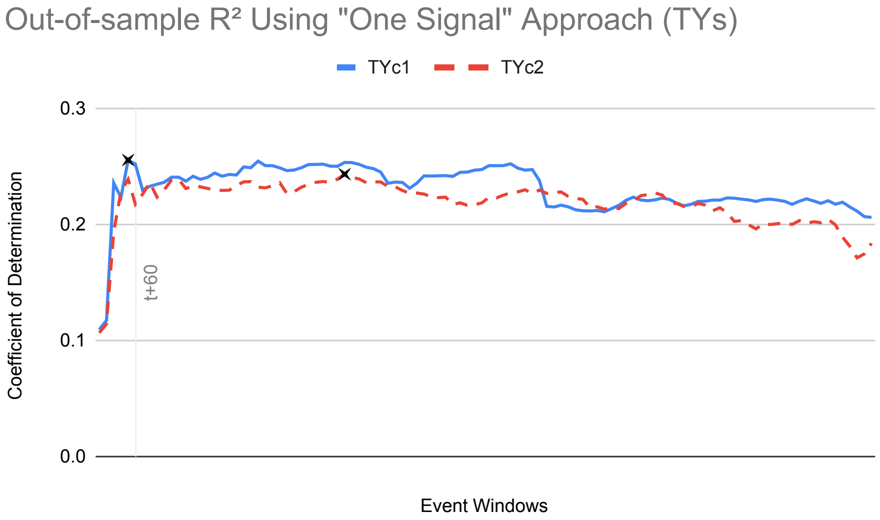


Testing R^2 Using "One Signal" Approach for 5-Year Treasury Futures



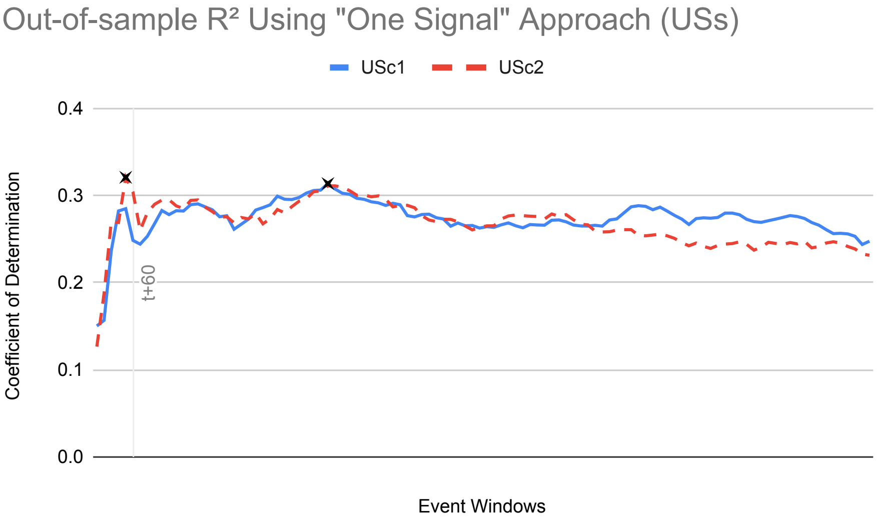
Testing R^2 Using "One Signal" Approach for 10-Year Treasury Futures

TYc2

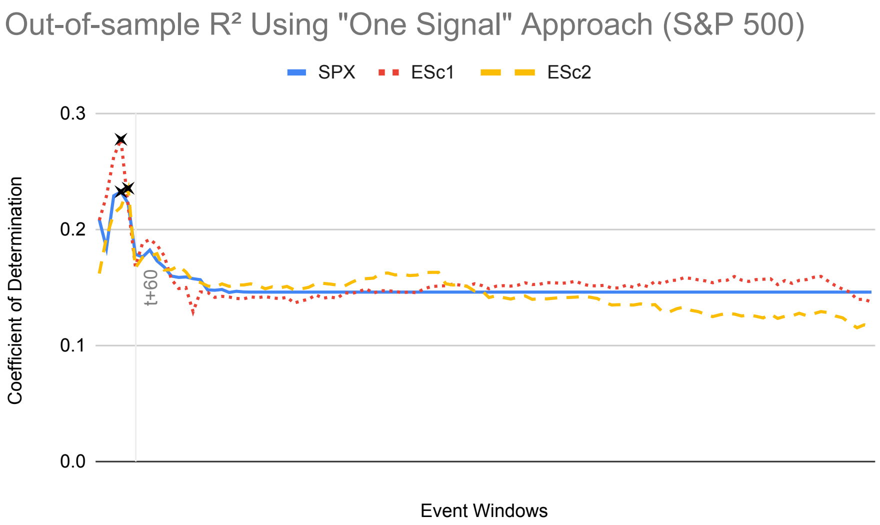


Testing R^2 Using "One Signal" Approach for 30-Year Treasury Futures

USc1



Testing R^2 Using "One Signal" Approach for S&P Index



TFIDF Equation

Back to Similarity

$$
\begin{aligned}
TFIDF_{d,t} &= tf_{d,t} * idf_{d,t} \\
&= \left[\ln\left(\frac{tc_{d,t}}{nt_d}\right) + 1\right] * \left[\ln\left(\frac{nd}{df_{d,t}+1}\right) + 1\right]
\end{aligned}
$$

- $tf_{d,t}$: Number of times term t is in document d
- nt_d: Number of terms in document d
- nd: Number of documents
- $df_{d,t}$: Number of documents term t appears in

TFIDF Informative Terms

Back to Similarity

- Additional pre-processing steps on FOMC statements:
  1. Make all words lowercase
  2. Remove words with little semantic meaning (e.g., articles)
  3. Convert all words into base terms (e.g., “increas”)

TFIDF Informative Terms

Back to Similarity

- Additional pre-processing steps on FOMC statements:
  1. Make all words lowercase
  2. Remove words with little semantic meaning (e.g., articles)
  3. Convert all words into base terms (e.g., "increas")

domestic	alreadytight	recov	tilt	buildup
alert	alter	foreign	imbal	undermin
direct	excess	quit	favor	perform
strength	fall	trend	eas	concern
background	firm	gener	demand	potenti
core	subdu	cost	longer	gain

Table 18: FOMC Statement Base Terms with Top 30 TFIDF Scores

Cosine Similarity Matrix

Back to Similarity