

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

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# Motivation

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

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- ▶ Useful for empirical macro: Obtain shocks from news to infer causal effects
  - Ex: Monetary policy (MP) announcements

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- ▶ 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?
  - Too short: Markets might **not fully react** to policy news yet
  - Too long: Change in price  $\approx$  MP shocks w/ **unrelated news, confounding factors**
  - **Just right:** Change in price  $\approx$  MP shocks with **minimised noise**

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- ▶ **Wrong A:** Contributes to MP shocks lacking precision because of noise

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  - NLP approximation → Text-based signal =  $\widehat{\Delta\text{Asset prices}}$  within given event window

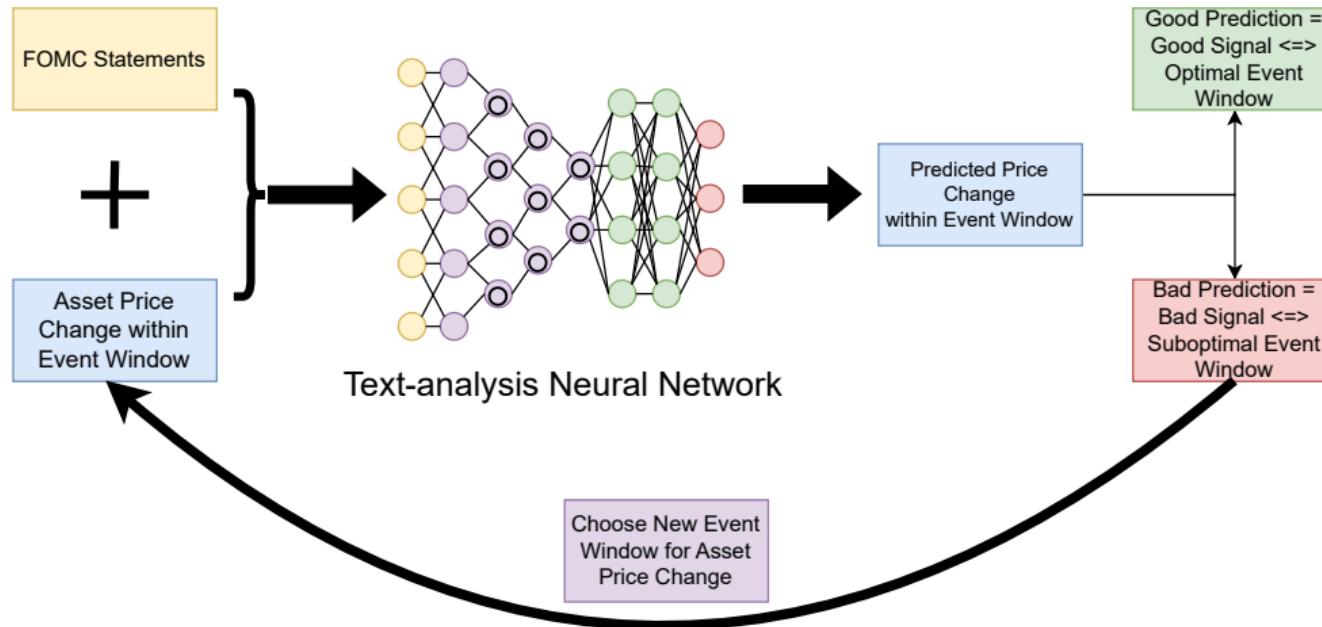
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  - Approximating underlying relationship  $f(\text{FOMC statement}) = \Delta\text{Asset prices}$
  - NLP approximation → Text-based signal =  $\widehat{\Delta\text{Asset prices}}$  within given event window
    - 1. **Optimal window only:** Noise has min average impact on  $\Delta\text{asset prices}$
    - 2. **Optimal window only:** NLP text-based signal has highest precision
    - 3. **Any other window:** Bad approximation by NLP → Bad signal

# This Paper

UAT + Layers

- ▶ **This Paper:** Estimate optimal window size for FOMC statements using NLP



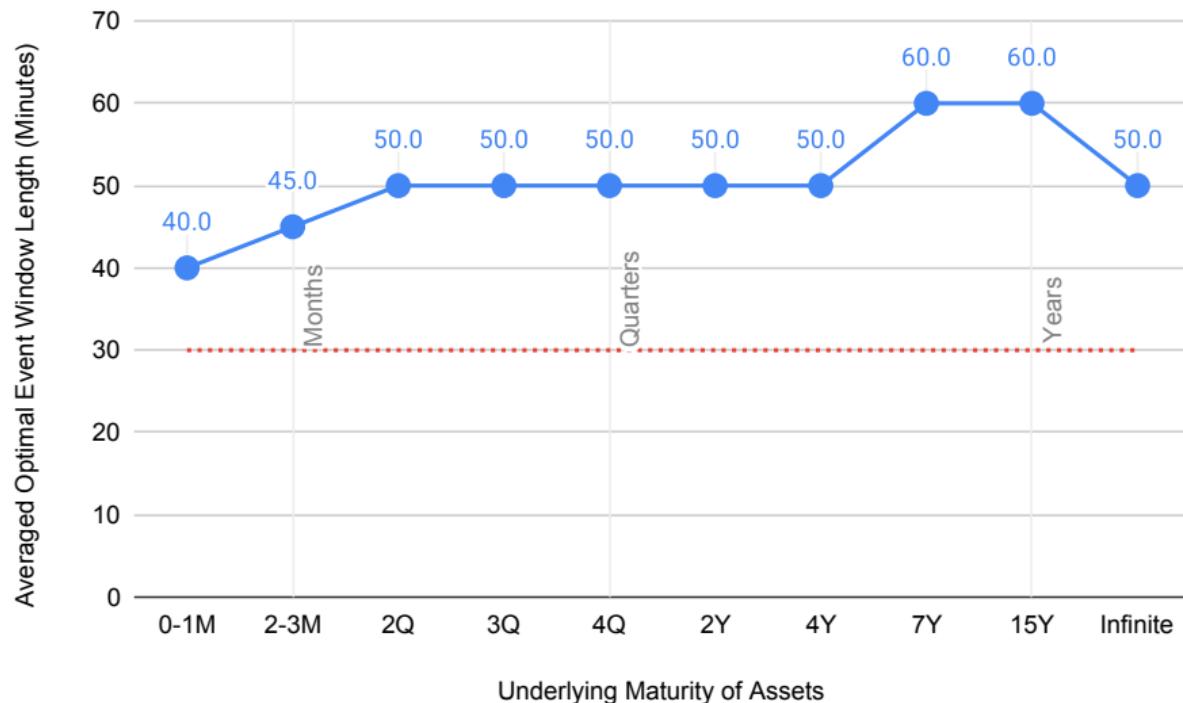
# Previous of Results: Summary

- ▶ **How Long?** Longer than literature standard of 30 minutes:
  - On avg, markets fully react within window 10 min before and 30+ min after
  - Underlying maturity of assets ↑, then average optimal window length ↑
  - Underlying maturity of asset at least 2 quarters out → 50- to 60-min window
  - Complex/dissimilar/dissent statements → Relatively longer windows

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  - Complex/dissimilar/dissent statements → Relatively longer windows
- ▶ **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 and stock prices

# 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 → Method can estimate optimal window; (2) Introduce noise min. approach

# Related Literature and Contributions

## 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:** ↑ 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); Nakamura and Steinsson (2018); Swanson and Jayawickrema (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 less dampened

# Presentation Roadmap

- ① Introduction
- ② Motivating Framework
- ③ Optimal Event Windows
- ④ MP Surprises & Shocks
- ⑤ Statement Characteristics

# Motivation: Why the Need for NLP?

- ▶ News is released  $\implies$  Markets react to news
  - Cognitive noise  $\rightarrow$  Markets might need more time to react
  - Too much time  $\rightarrow$  Introduce unrelated news
- ▶ Therefore: How to choose optimal time window with minimal noise?
- ▶ Simple Framework: Show how noise components impact price and time window
  - Strong assumptions to illustrate points
  - Motivate the need for NLP method with FOMC statements

# Motivating Framework of Asset Market Prices (1/4)

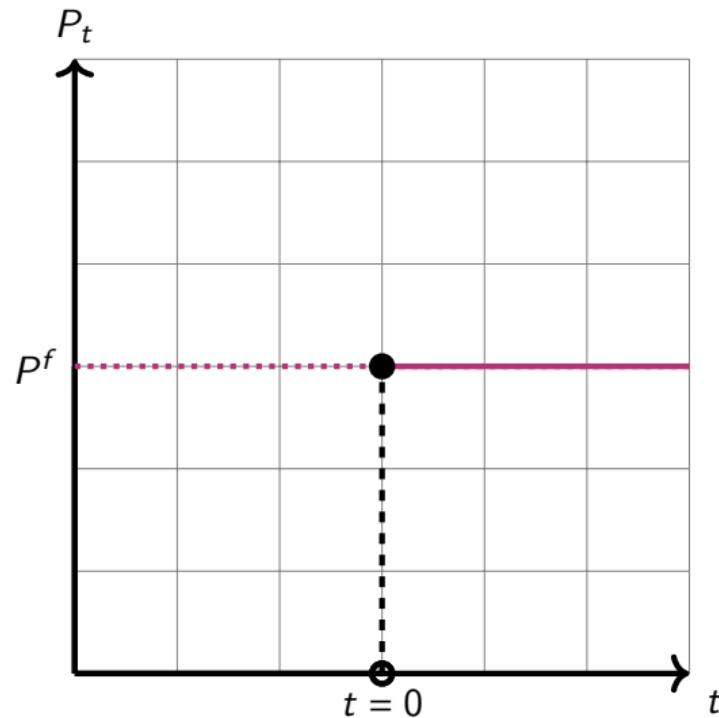
$$\{P_t = P_t^f + \varepsilon_t^c + \varepsilon_t^n | t \geq 0\}, \quad (1)$$

- ▶ Fundamental price component:  $P_t^f = P^f \in \mathbb{R}$
- ▶ **Interpretation:** Price **because of** news

# Impulse Response Scenarios of Asset Prices (1/4)

## Scenario 1. 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
- Choose shortest event window



# Motivating Framework of Asset Market Prices (2/4)

$$\{P_t = P_t^f + \varepsilon_t^c + \varepsilon_t^n | t \geq 0\}, \quad (2)$$

- ▶ Fundamental price component:  $P_t^f = P^f \in \mathbb{R}$
- ▶ Cognitive noise:  $\varepsilon_t^c = \rho_c \varepsilon_{t-1}^c + e^{-\mathcal{D}t} \nu_t^c$

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:  $\text{Var}(\varepsilon_0^c) = \sigma_c^2$

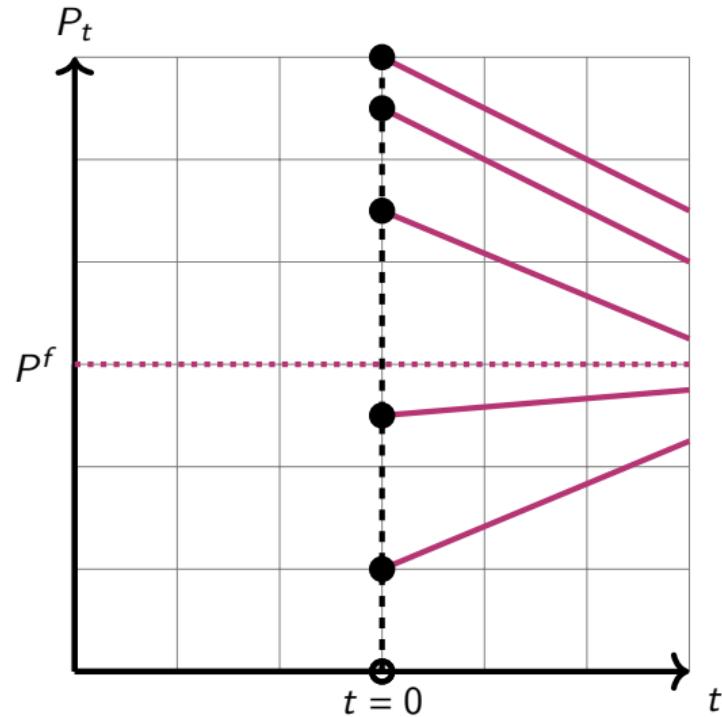
- ▶  $\varepsilon_t^c$  and its error decay to zero

# Impulse Response Scenarios of Asset Prices (2/4)

## Scenario 2. Cognitive noise + No unrelated news

Interpretations

- ▶  $P_t$  jumps anywhere because of cognitive noise
- ▶  $P_t \rightarrow P^f$  because of no unrelated news
- Choose long event window



# Motivating Framework of Asset Market Prices (3/4)

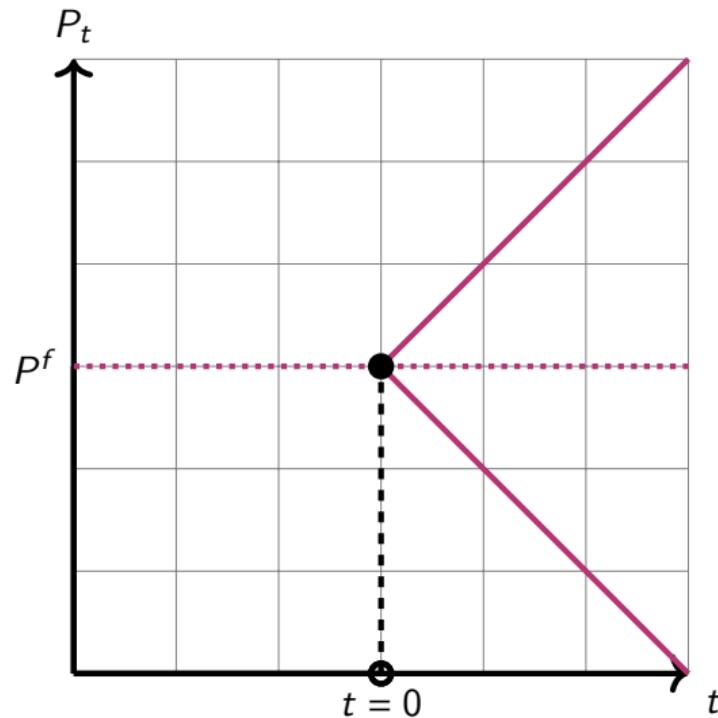
$$\{P_t = P_t^f + \varepsilon_t^c + \varepsilon_t^n | t \geq 0\}, \quad (3)$$

- ▶ Fundamental price component:  $P_t^f = P^f \in \mathbb{R}$
- ▶ Unrelated news:  $\varepsilon_t^n = \varepsilon_{t-1}^n + \nu_t^n$ 
  - $\nu_t^n \sim \mathcal{N}(0, \sigma_n^2)$
  - Assumption:  $\text{Var}(\varepsilon_0^n) = 0$

# Impulse Response Scenarios of Asset Prices (3/4)

## Scenario 1. No cognitive noise + Unrelated news

- ▶  $P_t \rightarrow P^f$  :: no cognitive noise
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- ▶ ∴ Choose short event window



# Motivating Framework of Asset Market Prices (4/4)

$$\{P_t = P_t^f + \varepsilon_t^c + \varepsilon_t^n | t \geq 0\}, \quad (4)$$

- ▶ Fundamental price component:  $P_t^f = P^f \in \mathbb{R}$
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  - $\nu_t^c \sim \mathcal{N}(0, \sigma_c^2)$
  - $|\rho_c| < 1$
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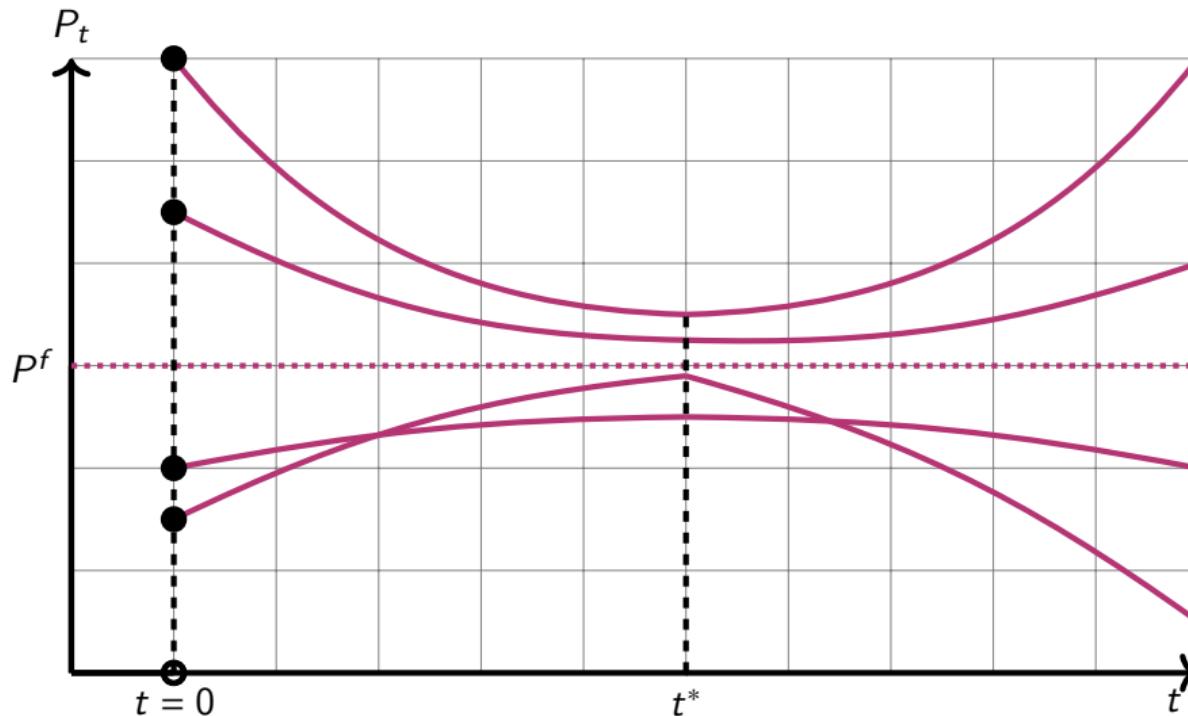
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- ▶ Cognitive noise:  $\varepsilon_t^c = \rho^c \varepsilon_{t-1}^c + e^{-\mathcal{D}t} \nu_t^c$
- ▶ Unrelated news:  $\varepsilon_t^n = \varepsilon_{t-1}^n + \nu_t^n$
- ▶ **Goal:** If “good” signal exists → Estimate time window reflecting full market reactions

Interpretations

# Impulse Response Scenarios of Asset Prices (4/4)

Scenario 3. Cognitive noise + Unrelated news



# Single News: Effects of Noise Components on $t^{one}$

[Derivation](#)

- ▶ Single news  $\rightarrow P^f$  moves  $\rightarrow \text{Var}(P_t | t \geq 0)$  moves  $\rightarrow$  Find **minimising time  $t^{one}$**

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- ▶ Single news  $\rightarrow P^f$  moves  $\rightarrow \text{Var}(P_t | t \geq 0)$  moves  $\rightarrow$  Find **minimising time  $t^{one}$**
- $\rightarrow \frac{\partial t^{one}}{\partial \sigma_n^2} < 0$
- $\rightarrow \frac{\partial t^{one}}{\partial \sigma_c^2} > 0$

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- $\rightarrow \frac{\partial t^{one}}{\partial \sigma_n^2} < 0$
- $\rightarrow \frac{\partial t^{one}}{\partial \sigma_c^2} > 0$
- ▶ Therefore,  $t^{one}$  moves by noise components<sup>†</sup>

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<sup>†</sup>I numerically verify the dynamics of the  $t^{one}$  for various values of  $\sigma_c^2$  and  $\sigma_n^2$  in the indirect expression whilst holding the other parameters constant.

# Multiple News: Estimator Form

- ▶ Current expressions for  $\text{Var}(P_t | t \geq 0)$ ,  $t^{\text{one}}$ : **One** news event
- ▶ **Problem:**  $N$  announcements and one asset price:
- ▶ **Goal:** Choose time window  $t^*$  such that

$$t^* : \min_t \sum_{i=1}^N \frac{1}{N} \left( P_{i,t} - P_{i,t}^f \right)^2$$

- ▶ However, assume  $P_{i,t}^f$  is **unobservable**. Instead, noisy signal  $s_i = P_i^f + \xi_i$  is observed
  - Observed by econometrician
  - $\xi_i \sim \mathcal{N}(0, \sigma_s^2)$

# Multiple News: MSE Minimisation Problem with Signal

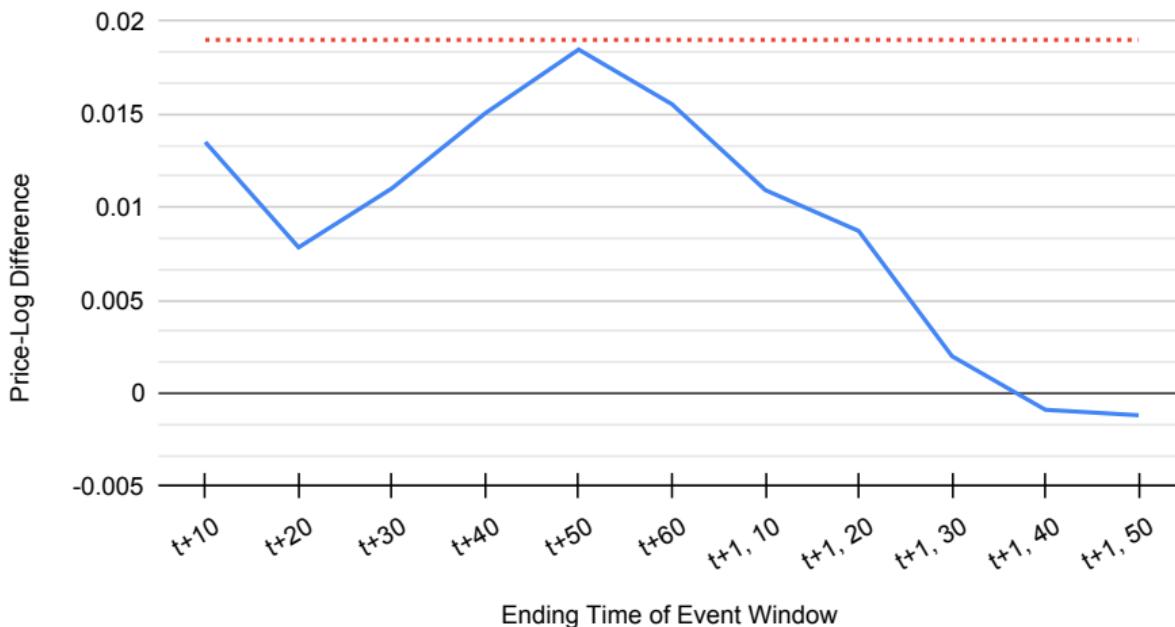
[Derivation](#)

$$t^* : \min_t \frac{1}{N} \sum_{i=1}^N (P_{i,t} - s_i)^2 \implies \min_t \left[ \frac{1}{N} \sum_{i=1}^N (\varepsilon_{i,t}^c + \varepsilon_{i,t}^n)^2 + \sigma_s^2 \right] \quad (5)$$

- ▶ With noisy signal  $s_i$ , MSE minimisation problem is the **same** as that with  $P_{i,t}^f$ 
  - Asymptotic result: Quality of signal doesn't matter
- ▶  $\implies$  Possible to estimate optimal  $t^*$  ( $\hat{t}$ ) with  $s_i$ 
  - Finite samples: Precision of  $s_i$  matters  $\rightarrow$  “**good**” signal matters

# Multiple News: Example of Signal in Financial Prices

Market Price Reactions for S&P 500 Index, 30/01/2008



# Motivating Framework Takeaways

- ▶ Simulated MSEs using  $P_{i,t}^f, s_i$  for different market scenarios
  - 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
- ▶  $\hat{t} \approx t^*$  in all scenarios
  - “Good” signal → Possible to estimate time horizon reflecting market full reactions
  - MP shocks = Finite sample problem → “Good” signal matters

Simulations

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- ▶ **Q:** How to get “good” signal for MP announcements?
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- ▶ **Reality:** Do not know noise processes
  - NLP method can estimate optimal window length without knowing

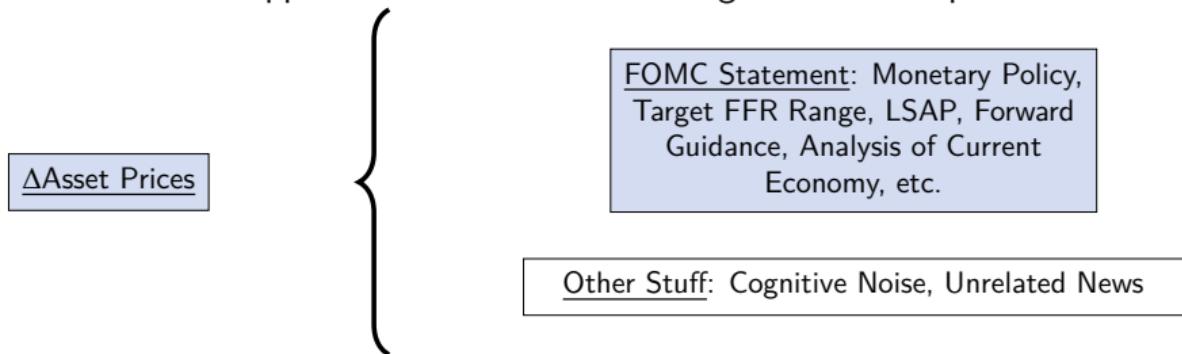
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# Estimating Optimal Event Windows from FOMC Statements: Overview

## 1. Apply text-analysis neural network to:

- Approximate **underlying** relationship  $f(\text{FOMC statement}) = \Delta\text{Asset prices}$
- Isolate  $\Delta\text{asset prices}$  **within given event window** to “full” FOMC statement text
  - ⇒ “Using **only** the entire FOMC statement, what is your predicted price change?”
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## 2. Regress $\Delta\text{asset prices}$ within **different** event windows on FOMC statements

## 3. Find event window where neural network has **highest predictive performance**

- **Optimal window only:** Noise components have **min average impact** on  $\Delta\text{asset prices}$
- **Optimal window only:** Neural network signal has **highest** precision
- **Any other window:** Bad approximation by neural network → **Bad signal**

# Estimating Optimal Event Windows: Variables and Approach

- ▶ **Approach:** Approximate  $f(\text{Inputs}) = \text{Outputs}$ 
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  - 165 statements from May 1999 - October 2019 FOMC Statement Ex Why FOMC Statements?

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- ▶ **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*

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# Estimating Optimal Event Windows: Approach

- ▶ **At the Core:**  $f(\text{FOMC statement text}) = DP_{t+n}$ : 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:
  - Quantify all info. in text (e.g., Word interdependencies, context, long-term memory)  
⇒ Approximate  $f(\text{FOMC statement text}) = DP_{t+n}$

Popular Method Ex Issues

# Estimating Optimal Event Windows: Approach

- ▶ **At the Core:**  $f(\text{FOMC statement text}) = DP_{t+n}$ : Nonparametric mapping
  - ▶ Popular methods cannot quantify  $f(\text{FOMC statement text}) = DP_{t+n}$
  - ▶ **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](#)
- ⇒ “Good” signal based on FOMC statement text within given window length
- ⇒ “Jointly” estimate optimal window and “good” signal

# Estimating Optimal Event Windows: Prepare for Train + Eval XLNet

- ▶ **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

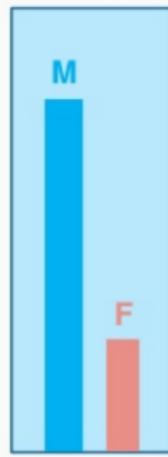
- ▶ **Goal:** “Good” signal from XLNet-Base for every FOMC statements
  - Method from ML literature: Train XLNet-Base on **splits** of data
- ▶ Split data into training (80%) and testing (20%) samples **5 times**:
  - By **stratified sampling**Why Stratified? Why CV?
  - Conditions: Word count (200-word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

# Estimating Optimal Event Windows: Prepare for Train + Eval XLNet

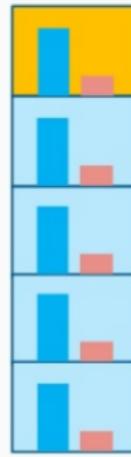
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[Why Stratified?](#) [Why CV?](#)
  - Conditions: Word count (200-word bins), FFR decision, FOMC chair, pre/post 2007
  - Every testing subsample share **NO** FOMC statements
- ▶ **Result:** XLNet-Base learns  $f(\text{FOMC statement text}) = DP_{t+n}$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

# Estimating Optimal Event Windows: Stratified CV Visual



Class Distributions



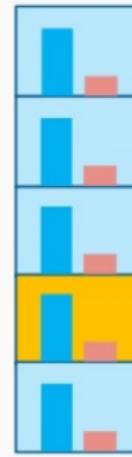
Round 1



Round 2



Round 3



Round 4



Round 5

# Estimating Optimal Event Windows: Accuracy Metrics

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- ▶ Make adjustments from typical definition because:

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- ▶ **Other Tracked Metrics:**  $\rho_{OOS}$ ,  $\widehat{MAE}_{OOS}$ ,  $\widehat{MSE}_{IS}$

# Estimating Optimal Event Windows: Loop “Diagram”

For each interest-rate and equity futures contract:

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

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  - 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 → Choose hyperparameters that yield highest  $R^2_{OOS}$

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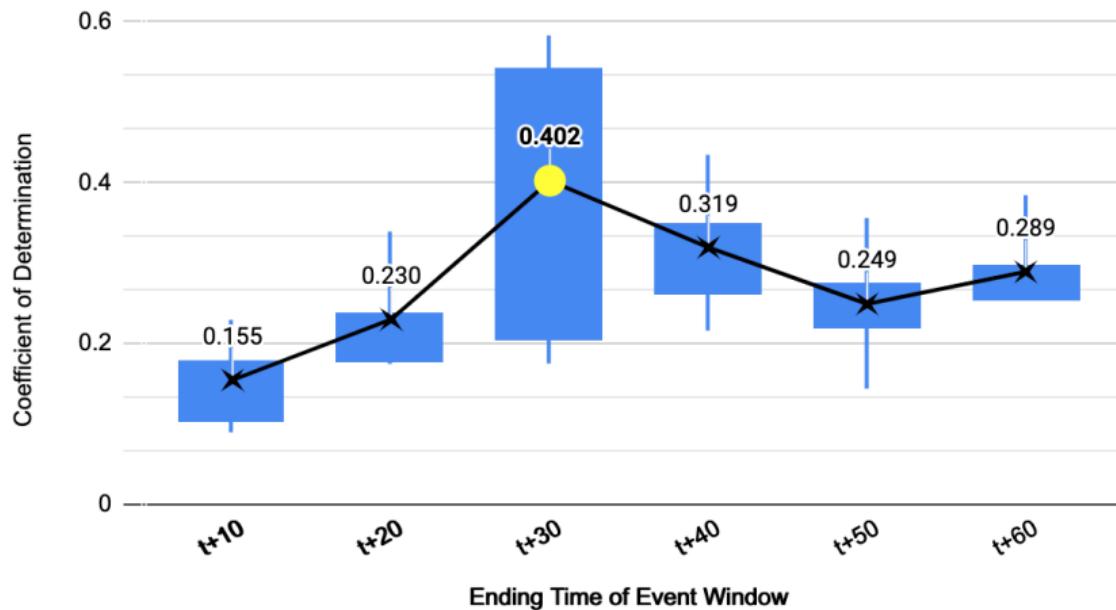
For each interest-rate and equity futures contract:

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    2. Evaluate NN on testing data → 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<sup>th</sup>, 25<sup>th</sup> percentiles

# Optimal Event Windows: FF3

Summary Visual

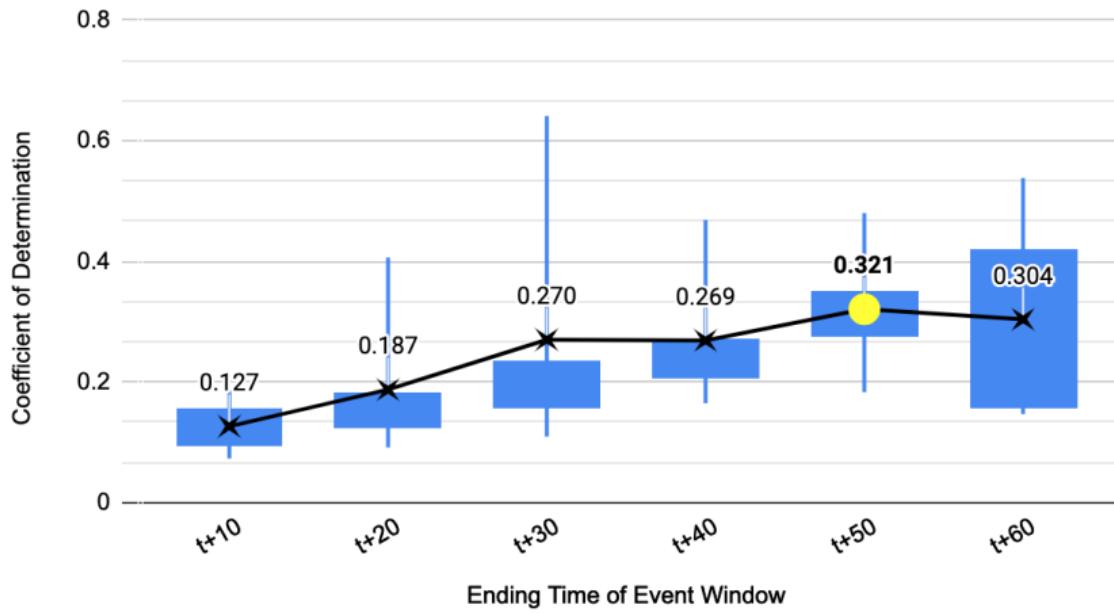
Out-of-sample R<sup>2</sup> for FF3 (Averaged Across Splits)



# Optimal Event Windows: USc2

Summary Visual

Out-of-sample R<sup>2</sup> for USc2 (Averaged Across Splits)



# Optimal Event Windows: Summary

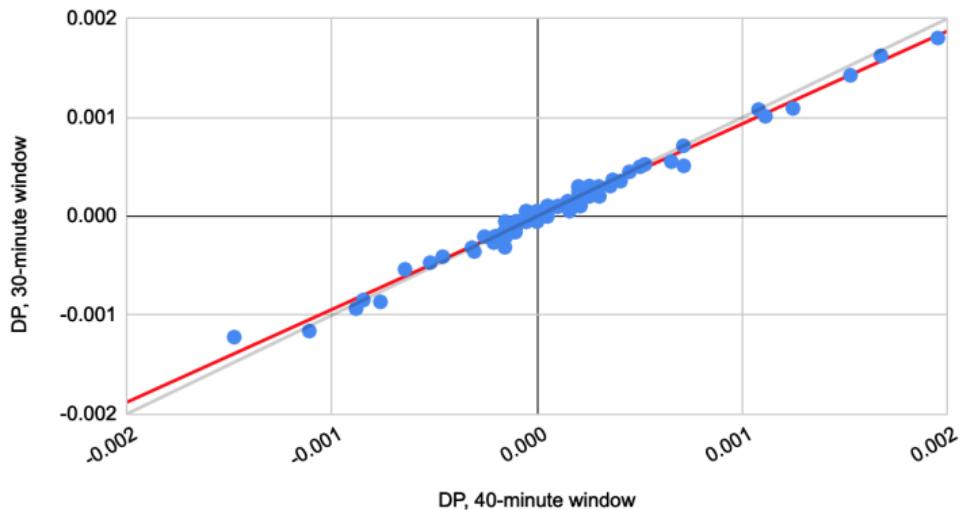
## ► How Long? Longer than 30 minutes:

[Other Assets](#)[Summary Visual](#)[Summary Table](#)[Recap](#)

- On avg, markets fully react within window 10 min before and 30+ min after
- $\overline{R^2_{OOS}}$  ↑ by 2–17% when event window ↑ to 40+ min
- Underlying maturity of assets ↑ → Avg optimal window length ↑
- Underlying maturity of asset at least 2 quarters out → 50- to 60-min window

# Optimal Event Windows: Diff Windows, Diff Responses (FF3\*\*\*)

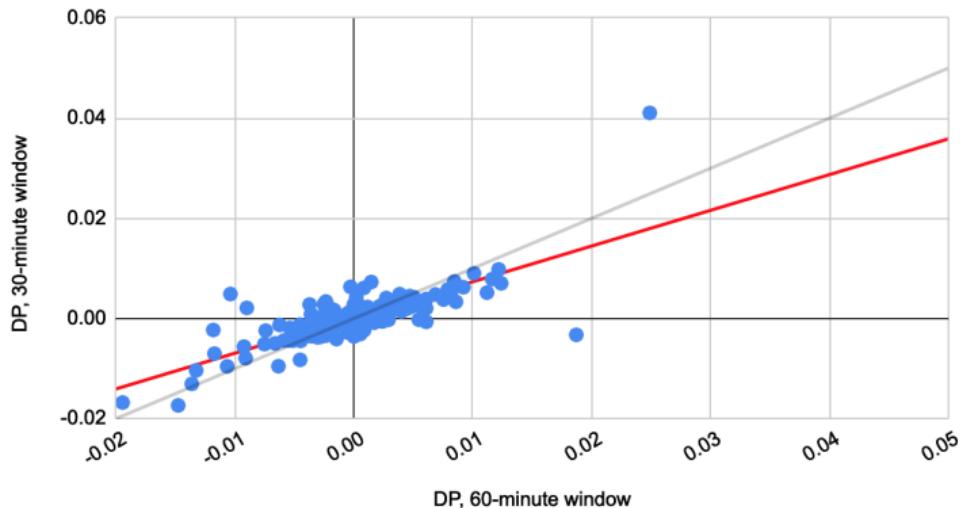
Market Responses in Different Event Windows (FF3)



- ▶ **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 ( $USc2^{***}$ )

Market Responses in Different Event Windows ( $USc2$ )



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# Overall Recap

[Summary Visual](#)[Summary Text](#)[Summary Table](#)

- ▶ Optimal event window lengths **longer** than literature standard of 30 minutes
- ▶ Diff underlying maturity of assets → Diff optimal windows
- **What happens to MP surprises and shocks?**

# Presentation Roadmap

- ① Introduction
- ② Motivating Framework
- ③ Optimal Event Windows
- ④ MP Surprises & Shocks
- ⑤ Statement Characteristics

# Monetary Policy Surprises: Overview

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*DP → Surprise*

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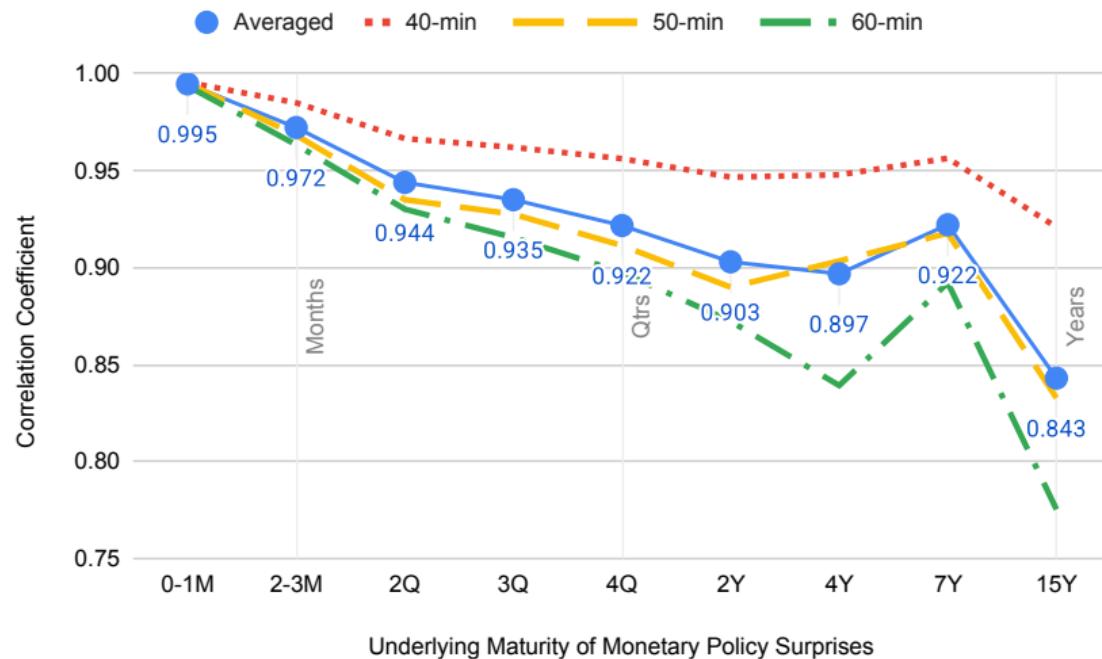
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- 3. Calculate correlations between MP surprise sets
- 4. Back to step 1

*DP → Surprise*

# Monetary Policy Surprises: Correlations Along the Yield Curve



→ Changing only window length has ↑ effect at **further horizons**

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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):
    - $GSS_T$  → 1<sup>st</sup> Principal component rotated to drive  $mp1$
    - $GSS_P$  → 2<sup>nd</sup> Principal component rotated to have no effect on  $mp1$
  2. Nakamura and Steinsson (2018):
    - $NS_{MP}$  → 1<sup>st</sup> Principal component of MP surprises
  3. Jarociński and Karadi (2020):
    - $JK_{MP}$  → 1<sup>st</sup> Principal component of MP surprises w/  $SPX$  + co-movement
    - $JK_{CBI}$  → 1<sup>st</sup> 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

# Monetary Policy Shock: Effects on Interest Rates and Equities

## ► LHS variables:

1.  $\Delta TY^i$  = 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.  $DP_{SPX}$  = Price log-difference of *SPX* within 30-minute and optimal windows
4.  $DP_{ESc1}$  = Price log-difference of *ESc1* within 30-minute and optimal windows
5.  $DP_{ESc2}$  = Price log-difference of *ESc2* within 30-minute and optimal windows

## ► Specification:

$$y^j = \beta_0^{j,k,l} + \beta_1^{j,k,l} (\text{Shock})^{k,l} + \varepsilon^{j,k,l}, \quad (6)$$

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

# MP Shocks: Nominal Interest Rates

	30-minute Window				Optimal Window				Difference		
	$\Delta TY_1$	$\Delta TY_2$	$\Delta TY_5$	$\Delta TY_{10}$	$\Delta TY_1$	$\Delta TY_2$	$\Delta TY_5$	$\Delta TY_{10}$	$\Delta TY_2$	$\Delta TY_5$	$\Delta TY_{10}$
$GSS_T$	1.00*** (0.28)	0.82*** (0.34)	0.15 (0.43)	-0.37 (0.41)	1.00*** (0.23)	0.78*** (0.28)	0.08 (0.33)	-0.42 (0.32)	<b>-0.04</b>	<b>-0.07</b>	<b>-0.05</b>
$GSS_P$	1.00*** (0.09)	1.46*** (0.09)	1.89*** (0.25)	1.64*** (0.36)	1.00*** (0.11)	1.51*** (0.10)	1.92*** (0.21)	1.66*** (0.30)	<b>+0.05</b>	<b>+0.04</b>	<b>+0.02</b>
$NS_{MP}$	1.00*** (0.08)	1.24*** (0.09)	1.29*** (0.19)	0.94*** (0.25)	1.00*** (0.09)	1.30*** (0.10)	1.39*** (0.18)	1.06*** (0.24)	<b>+0.06</b>	<b>+0.11</b>	<b>+0.11</b>
$JK_{MP}$	1.00*** (0.11)	1.30*** (0.15)	1.39*** (0.28)	0.99*** (0.36)	1.00*** (0.12)	1.35*** (0.16)	1.52*** (0.32)	1.16*** (0.43)	<b>+0.04</b>	<b>+0.13</b>	<b>+0.17</b>
$JK_{CBI}$	1.00*** (0.25)	1.04*** (0.30)	1.00*** (0.31)	0.82*** (0.29)	1.00*** (0.23)	1.20*** (0.25)	1.14*** (0.27)	0.85*** (0.26)	<b>+0.16</b>	<b>+0.14</b>	<b>+0.03</b>

Table 1: Diff in Responses of Nominal Interest Rates to Shocks from Event Window Choice

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

# MP Shocks: Real Interest Rates

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

Table 2: 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: Stock Prices

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

Table 3: 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

# Presentation Roadmap

- ① Introduction
- ② Motivating Framework
- ③ Optimal Event Windows
- ④ MP Surprises & Shocks
- ⑤ Statement Characteristics

# Estimating Optimal Event Windows: “Joint” and “One Signal” Approaches

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

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  - GPU + Financial constraints = Estimate optimal window lengths only up to  **$t + 60$**
  - Current computation time: **249+ days**
- ▶ **Assumption:** NN Predictions in “joint-estimated” event window = **Constant  $\forall t^\ddagger$** 
  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

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<sup>†</sup>Signal from XLNet-Base is likely to change ∵ 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

- ▶ 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 text 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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  - Range of reading Levels: 12.2–21.3
  - Median Reading Level: 16.5

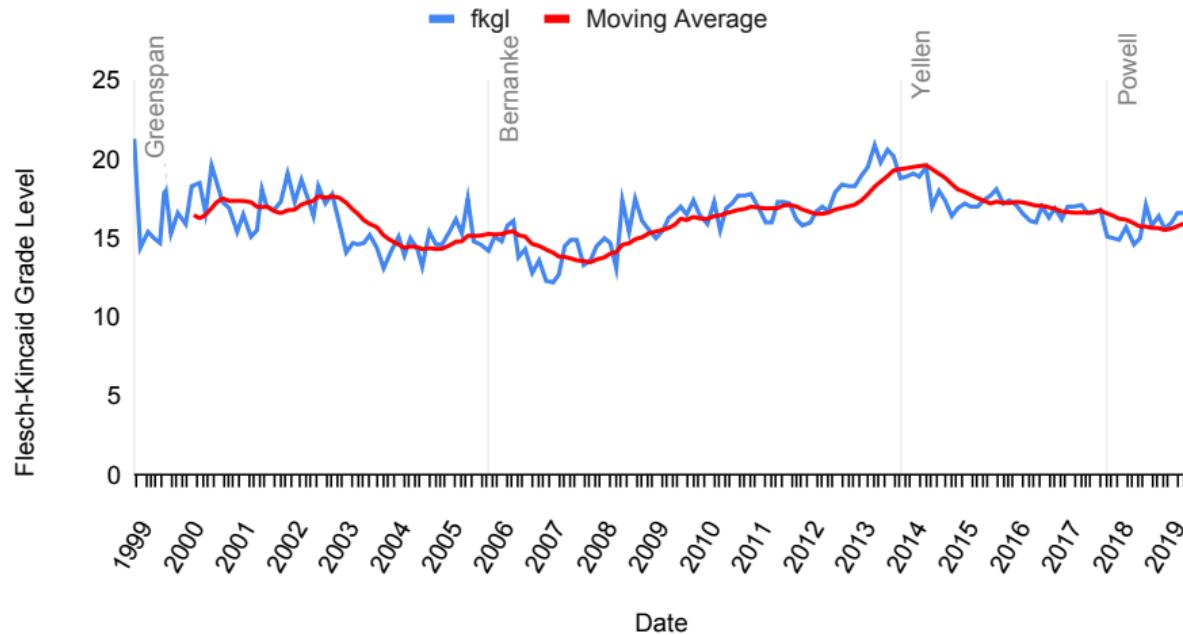
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  - Range of reading Levels: 12.2–21.3
  - Median Reading Level: 16.5
- ▶ Split sample conditioned on being  $\leq$  or  $>$  16.5
- ▶ Calculate sub-set MSEs and event window lengths

# FOMC Statement Characteristics: Text Complexity (2/3)

Flesch-Kincaid Grade Level Readability of FOMC Statements



# FOMC Statement Characteristics: Text Complexity (3/3)

Metric	Simple	Complicated
<i>Minimised MSE</i>		
Average	1.26e-5	<b>1.03e-5</b>
<i>Event Window Length (Minutes)</i>		
Average	59	<b>71</b>

Table 4: Average MSEs and Event Window Lengths Using the “One Signal” Approach, Conditioned by FOMC Statement Complexity

→ FOMC statements with ↑ complexity → 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...

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- ▶ Measured based on Term Frequency-Inverse Document Frequency (TFIDF)
  - Weighted frequency assigned to terms based on:
    1. Number of times term appears in a document
    2. Number of documents terms appears in

[TFIDF Equation](#)

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- ▶ Terms with  $\uparrow TFIDF_{d,t}$  = Informative terms at **distinguishing** documents  $d$ 
  - [TFIDF Terms](#)

[TFIDF Equation](#)

# FOMC Statement Characteristics: Text Similarity (2/4)

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

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- ▶  $\Rightarrow TFIDF \cdot TFIDF^T =$  Dot product between every **pair** of FOMC statements
- ▶  $\Rightarrow$  Degree of similarity between 2 FOMC statements = **Cosine similarity**:

Similarity Matrix

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

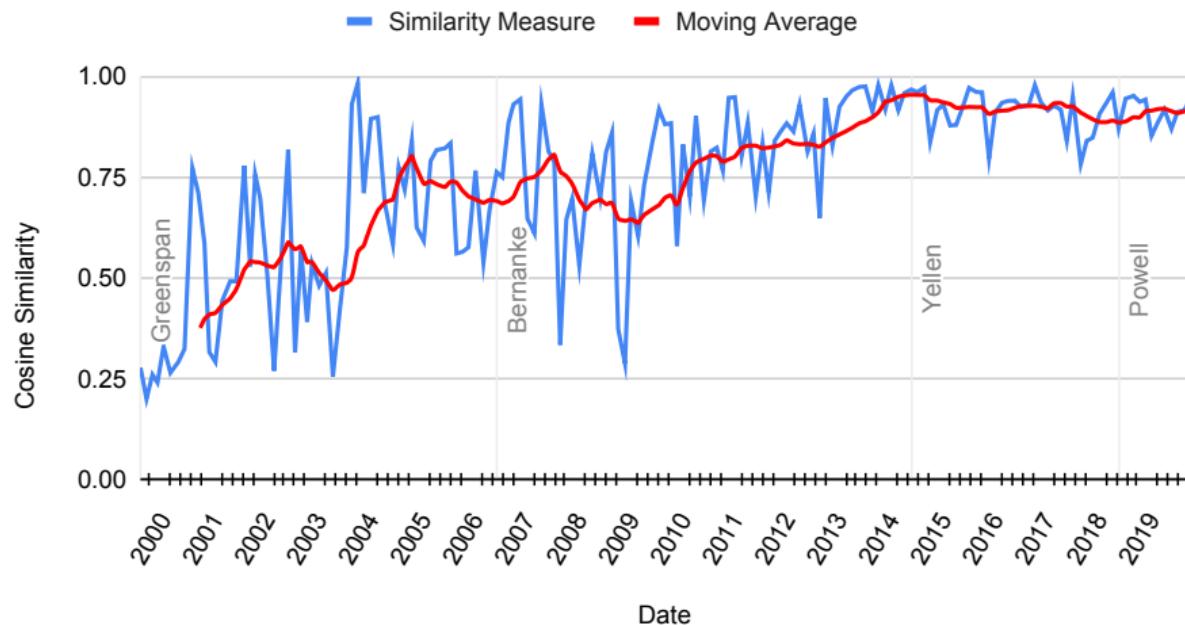
- ▶ **Scale:** Entirely different  $= 0 \leq$  Cosine Similarity  $\leq 1 =$  Exact same

# FOMC Statement Characteristic: Text Similarity (3/4)

- ▶  $S^1 := (d, d - 1)$ : Degree of similarity between sequential FOMC statements
  - 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)

## Cosine Similarity of Sequential FOMC Statements



# FOMC Statement Characteristics: Text Similarity (4/4)

Metric	Different	Similar
<i>Minimised MSE</i>		
Average	<b>1.14e-5</b>	1.14e-5
<i>Event Window Length (Minutes)</i>		
Average	<b>61</b>	51

Table 5: 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<sup>§</sup>
  - Riboni and Ruge-Murcia (2014); Tsang and Yang (2024); Bobrov et al. (2025); and others...

---

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- ▶ Condition FOMC statements based presence of dissent votes or not<sup>§</sup>
  - 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

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[Back to Characteristics](#)

- ▶ Condition FOMC statements based presence of dissent votes or not<sup>§</sup>
  - 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

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<sup>§</sup>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)

Metric	Unity	Dissents
<i>Minimised MSE</i>		
Average	9.21e-6	<b>1.44e-5</b>
<i>Event Window Length (Minutes)</i>		
Average	61	<b>83</b>

Table 6: Average MSEs and Event Window Lengths Using the “One Signal” Approach, Conditioned by Presence of Dissents in FOMC Statements

→ FOMC statements with dissents → longer event windows on average

# Conclusion

- ▶ **This Paper:** Estimate optimal window size for FOMC statements using NLP:
  - By combining **text-based signal** with observed price dynamics
  - Approximating **underlying** relationship  $f(\text{FOMC statement}) = \Delta\text{Asset prices}$
- ▶ **How Long?** **Longer** than literature standard of 30 minutes:
  - On avg, markets fully react within window 10 min before and **30+ min after**
  - Underlying maturity of assets ↑, then average optimal window length ↑
  - Underlying maturity of asset at least 2 quarters out → 50- to 60-min window
  - Complex/dissimilar/dissent statements → Relatively **longer** windows
- ▶ **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 and stock prices

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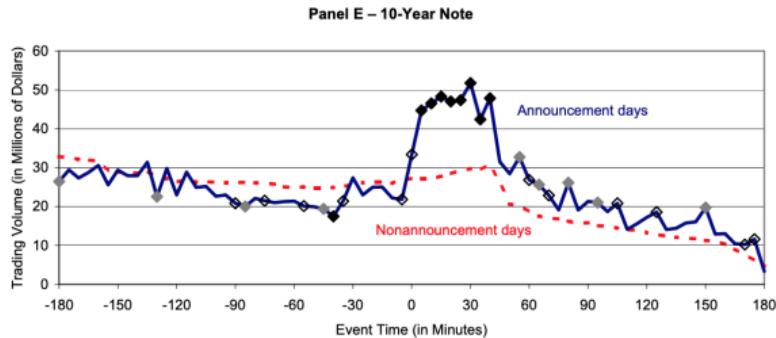
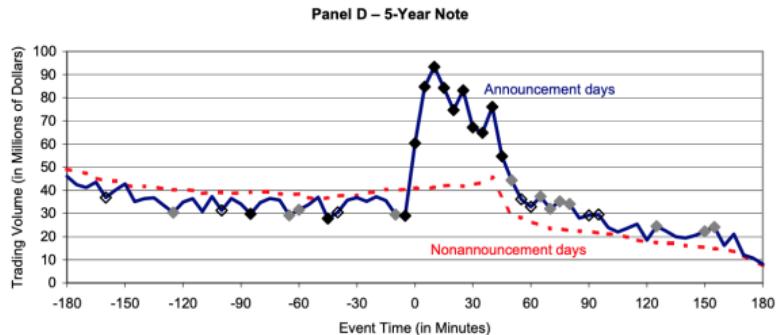
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# Liquidity: Related Symptom for Longer Event Windows (1/2)

[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

# Interpretations of Cognitive Noise

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)

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

$$\begin{aligned}\text{Var}(P_0) &= \text{Var}(\varepsilon_0^c) + \text{Var}(\varepsilon_0^n) \\ &= \sigma_c^2\end{aligned}$$

$$\begin{aligned}\text{Var}(P_1) &= \text{Var}(\varepsilon_1^c) + \text{Var}(\varepsilon_1^n) \\ &= \sigma_c^2(\rho_c^2 + e^{-2\mathcal{D}}) + \sigma_n^2\end{aligned}$$

$$\begin{aligned}\text{Var}(P_2) &= \text{Var}(\varepsilon_2^c) + \text{Var}(\varepsilon_2^n) \\ &= \sigma_c^2(\rho_c^4 + \rho_c^2 e^{-2\mathcal{D}} + e^{-4\mathcal{D}}) + 2\sigma_n^2\end{aligned}$$

⋮

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

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

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

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

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

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

$$\text{Var}(P_t|t \geq 0) = \overbrace{\left[ \frac{\rho_c^{2(t+1)} - e^{-2(t+1)\mathcal{D}}}{\rho_c^2 - e^{-2\mathcal{D}}} \right] \sigma_c^2 + t\sigma_n^2}^{\text{lim}_{t \rightarrow \infty} \text{ is } 0} \quad (7)$$

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

$$\text{Var}(P_t|t \geq 0) = \overbrace{\left[ \frac{\rho_c^{2(t+1)} - e^{-2(t+1)\mathcal{D}}}{\rho_c^2 - e^{-2\mathcal{D}}} \right] \sigma_c^2 + t\sigma_n^2}^{\lim_{t \rightarrow \infty} \text{ is } 0} \quad (7)$$

$$\implies t^{\text{one}} : \mathcal{D} [e^{-2(t+1)\mathcal{D}}] + \ln(\rho_c) \rho_c^{2(t+1)} = \left[ \frac{(e^{-2\mathcal{D}} - \rho_c^2)}{2} \right] \frac{\sigma_n^2}{\sigma_c^2} \quad (8)$$

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

$$\text{Var}(P_t|t \geq 0) = \overbrace{\left[ \frac{\rho_c^{2(t+1)} - e^{-2(t+1)\mathcal{D}}}{\rho_c^2 - e^{-2\mathcal{D}}} \right]}^{\text{lim}_{t \rightarrow \infty} \text{ is } 0} \sigma_c^2 + t\sigma_n^2 \quad (7)$$

$$\implies t^{\text{one}} : \mathcal{D} [e^{-2(t+1)\mathcal{D}}] + \ln(\rho_c) \rho_c^{2(t+1)} = \left[ \frac{(e^{-2\mathcal{D}} - \rho_c^2)}{2} \right] \frac{\sigma_n^2}{\sigma_c^2} \quad (8)$$

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

---

<sup>P</sup>Because Equation 3 is unable to have  $t$  isolated on one side, I numerically verify the dynamics of the  $t^{\text{one}}$  for various values of  $\sigma_c^2$  and  $\sigma_n^2$  in the indirect expression whilst holding the other parameters constant.

# Derivation of MSE Minimisation Problem with Signal

$$\begin{aligned}
 t^* : \min_t \frac{1}{N} \sum_{i=1}^N (P_{i,t} - s_i)^2 &= \min_t \frac{1}{N} \sum_{i=1}^N (P_i^f + \varepsilon_{i,t}^c + \varepsilon_{i,t}^n - P_i^f - \xi_i)^2 \\
 &= \min_t \frac{1}{N} \sum_{i=1}^N (\varepsilon_{i,t}^c + \varepsilon_{i,t}^n - \xi_i)^2 \\
 &= \min_t \frac{1}{N} \sum_{i=1}^N \left[ (\varepsilon_{i,t}^c + \varepsilon_{i,t}^n)^2 + \xi_i^2 - 2\xi_i (\varepsilon_{i,t}^c + \varepsilon_{i,t}^n) \right] \\
 &= \min_t \left\{ \mathbb{E} \left[ (\varepsilon_{i,t}^c + \varepsilon_{i,t}^n)^2 \right] + \mathbb{E} [\xi_i^2] - 2 \mathbb{E} [\xi_i] \mathbb{E} \left[ (\varepsilon_{i,t}^c + \varepsilon_{i,t}^n) \right] \right\} \\
 \implies t^* : \min_t \frac{1}{N} \sum_{i=1}^N (P_{i,t} - s_i)^2 &= \min_t \left[ \frac{1}{N} \sum_{i=1}^N (\varepsilon_{i,t}^c + \varepsilon_{i,t}^n)^2 + \sigma_s^2 \right]
 \end{aligned} \tag{9}$$

# Simulation Setup (1/3): Initial Conditions

- ▶  $t = 0$ : Release of **one** FOMC announcement

- $P_{t,i}^f = P_i^f \in [-100, 100]$
- $\varepsilon_{i,0}^c \in [-100, 100]$
- $\varepsilon_{i,0}^n = 0$
- $\sigma_s \in \mathbb{R}$

## Simulation Setup (2/3): MSEs

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

## Simulation Setup (3/3): Market Scenarios

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- ▶ 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
$\sigma_c$	100	0.1	50
$\mathcal{D}$	0.5	1	0.75
$\sigma_n$	0.1	10	1
$\rho_c$	0.47	0.47	0.47
$\sigma_s$	$\in \mathbb{R}$	$\in \mathbb{R}$	$\in \mathbb{R}$

Table 7: 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

	Scenario 1	Scenario 2	Scenario 3
<i>Simulation Parameters</i>			
$P_i^f$	$\in [-100, 100]$	$\in [-100, 100]$	$\in [-100, 100]$
$\varepsilon_{i,0}^c$	$\in [-100, 100]$	$\in [-100, 100]$	$\in [-100, 100]$
$\varepsilon_{i,0}^n$	0	0	0
$\sigma_c$	100	0.1	50
$\mathcal{D}$	0.5	1	0.75
$\sigma_n$	0.1	10	1
$\rho_c$	0.47	0.47	0.47
$\sigma_s$	$\in \mathbb{R}$	$\in \mathbb{R}$	$\in \mathbb{R}$
<i>Simulation Results</i>			
$t^*$	16	2	10
$\hat{t}$	15	2	10

Table 8: Framework Parameters and Results from 10,000 Simulations

# Preprocessing FOMC Statement Text

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- ▶ 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

# Cleaned FOMC Statement (09/2006)

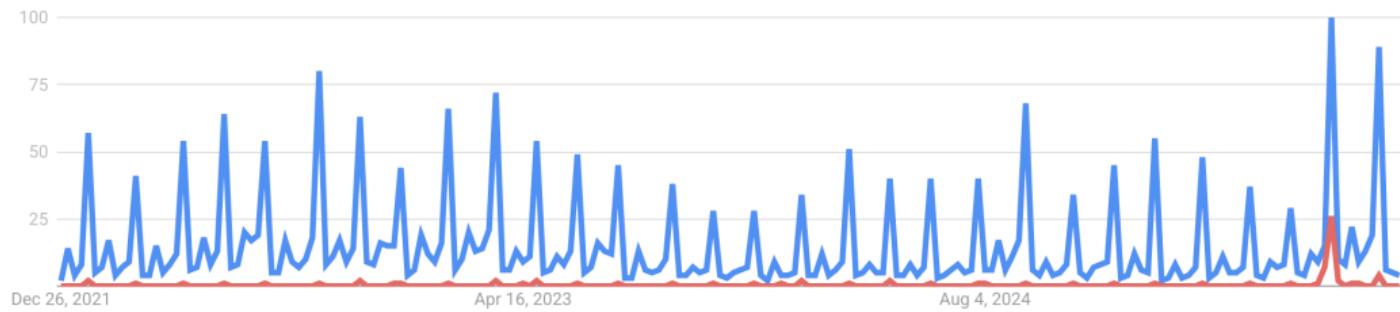
[Back to Results Preview](#)[Back to Variables](#)

1. The Federal Open Market Committee decided today to keep its target for the federal funds rate at 5-1/4 percent.
2. The moderation in economic growth appears to be continuing, partly reflecting a cooling of the housing market.
3. Readings on core inflation have been elevated, and the high levels of resource utilization and of the prices of energy and other commodities have the potential to sustain inflation pressures
4. However, inflation pressures seem likely to moderate over time, reflecting reduced impetus from energy prices, contained inflation expectations, and the cumulative effects of monetary policy actions and other factors restraining aggregate demand.
5. Nonetheless, the Committee judges that some inflation risks remain.
6. The extent and timing of any additional firming that may be needed to address these risks will depend on the evolution of the outlook for both inflation and economic growth, as implied by incoming information.

# Why FOMC Statements?

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- ▶ FOMC statements = Initial + Primary communication of MP
  - FOMC statement website = 1<sup>st</sup> – 3<sup>rd</sup> query on search engines



# Futures Contract Overview (1/2)

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- ▶ 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, Kisacikoglu, 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, Kisacikoglu, et al., 2020)

## Futures Contract Overview (2/2)

- ▶ 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, Kisacikoglu, 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, Kisacikoglu, et al., 2020)
- ▶ S&P 500 E-mini futures: Quarterly contracts that pay out  $50 \text{ USD} \times \text{S\&P 500}$  value on the last day of the expiry month (i.e., March, June, September, and December)

# NN Input/Output Visual

[Back to Variables](#)

- ▶ 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

$$\begin{bmatrix} x_i^1 & x_i^2 & x_i^3 & x_i^4 & x_i^5 & x_i^6 & \dots & x_i^{512} \end{bmatrix}$$

The    Federal    Open    Market    Committee    decided    .

- ▶  $x_t^0$  = 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

# 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 → Nothing about finding structure and training
- ▶ In reality, adding more layers:
  - ↓ number of parameters for each node function
  - ↓ 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 9:** 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 initialising 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 10:** 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 initialising 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](#)

# NN Training Overview

[Back to Loop](#)

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

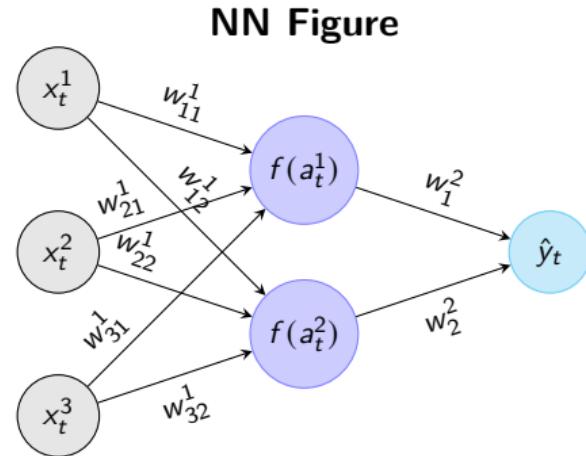
[Small NN Ex](#)

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 → update weights  $w$
- ▶ **Testing** prediction error → update network structure



**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 → Lower data requirements for NNs **BUT**
2. Large sample size for NNs → Fold  $\approx$  Population for characteristics
  - Can use random  $k$ -fold cross validation
3. Finite sample size for NNs  $\rightarrow$  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

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

$$R^2_{OOS} = 1 - \frac{\widehat{MSE}}{\widehat{MST}} = 1 - \frac{T^{-1} \sum_{i=1}^T (y_i - \hat{y}_i)^2}{\frac{T+1}{T(T-1)} \sum_{i=1}^T (y_i - \overline{y}_{IS})^2}, \quad (10)$$

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- ▶ **Interpretation:** % of null model's *MSE* explained by NN
  - NOT % of  $DP_{t+n}$  variance explained by NN ∵ nonlinearity

# Estimating Optimal Event Windows: Accuracy Metrics

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

$$R_{OOS}^2 = 1 - \frac{\widehat{MSE}}{\widehat{MST}} = 1 - \frac{T^{-1} \sum_{i=1}^T (y_i - \hat{y}_i)^2}{\frac{T+1}{T(T-1)} \sum_{i=1}^T (y_i - \overline{y}_{IS})^2}, \quad (10)$$

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- ▶ **Explicit objective function:** Minimise  $\widehat{MSE}$  during fine-tuning
  - $\min \widehat{MSE} = \max R_{OOS}^2$

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  - Null model:  $\overline{y}_{IS}$  as prediction
- ▶ **Interpretation:** % of null model's *MSE* explained by NN
  - NOT % of  $DP_{t+n}$  variance explained by NN :: nonlinearity
- ▶ **Explicit objective function:** Minimise  $\widehat{MSE}$  during fine-tuning
  - $\min \widehat{MSE} = \max R_{OOS}^2$
- ▶ **Other tracked metrics:**  $\rho_{OOS}$ ,  $\widehat{MAE}_{OOS}$ ,  $\widehat{MSE}_{IS}$

# 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 ↑ “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  $f(\text{FOMC statement text}) = DP_{t+n}$
  - Tuning process takes **1 computation day** for each  $DP_{t+n}$

[Back to Summary Text](#)

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

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

Table 11: Differences of  $\overline{R^2_{OOS}}$  between 30-minute and Optimal Event Windows (cont.)

[Back to Summary Text](#)

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

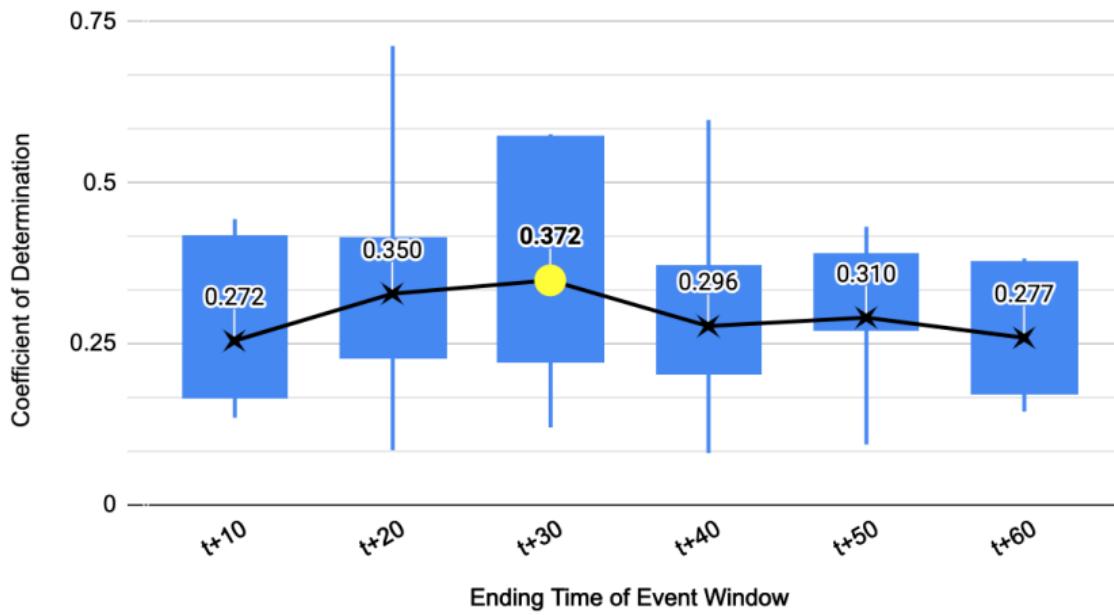
Asset	$\overline{R^2_{OOS}}$ , 30-min	$\overline{R^2_{OOS}}$ , Optimal	Difference
<i>FVc1</i>	11.7%	21.4%	+9.7 p.p.
<i>FVc2</i>	12.7%	19.2%	+6.5 p.p.
<i>TYc1</i>	11.7%	25.5%	+13.8 p.p.
<i>TYc2</i>	11.4%	23.9%	+12.5 p.p.
<i>USc1</i>	15.7%	28.5%	+12.8 p.p.
<i>USc2</i>	18.7%	32.1%	+13.4 p.p.
<i>SPX</i>	18.4%	23.2%	+4.8 p.p.
<i>ESc1</i>	22.9%	26.2%	+3.3 p.p.
<i>ESc2</i>	19.3%	23.5%	+4.2 p.p.

Table 12: Differences of  $\overline{R^2_{OOS}}$  between 30-minute and Optimal Event Windows

# Optimal Event Windows: FF1

[Back to Summary Text](#)

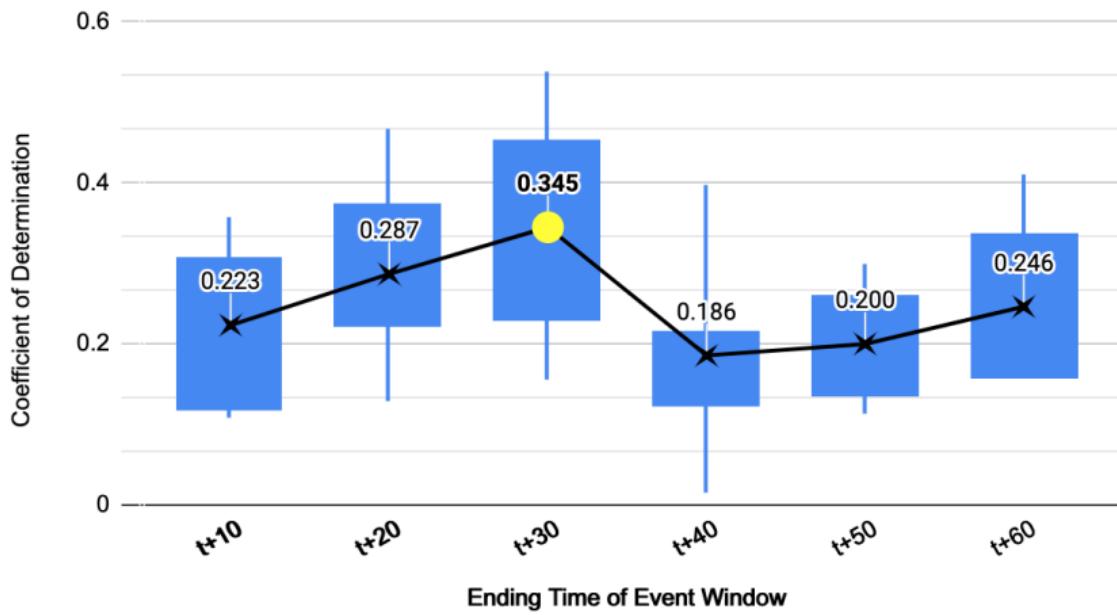
Out-of-sample R<sup>2</sup> for FF1 (Averaged Across Splits)



# Optimal Event Windows: FF2

[Back to Summary Text](#) [One Signal](#)

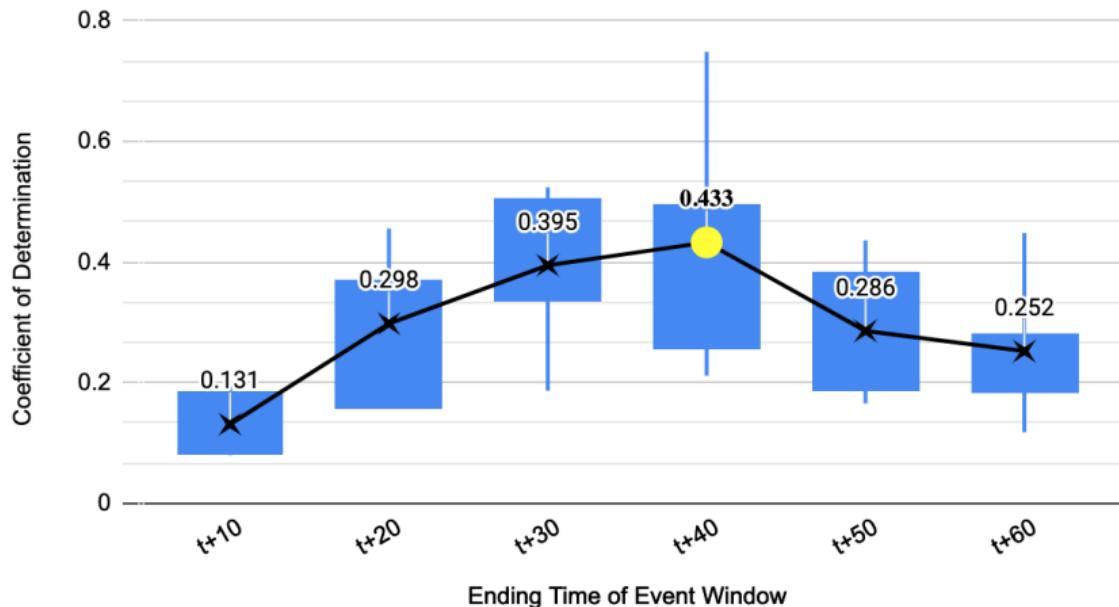
Out-of-sample R<sup>2</sup> for FF2 (Averaged Across Splits)



# Optimal Event Windows: FF4

[Back to Summary Text](#) [One Signal](#)

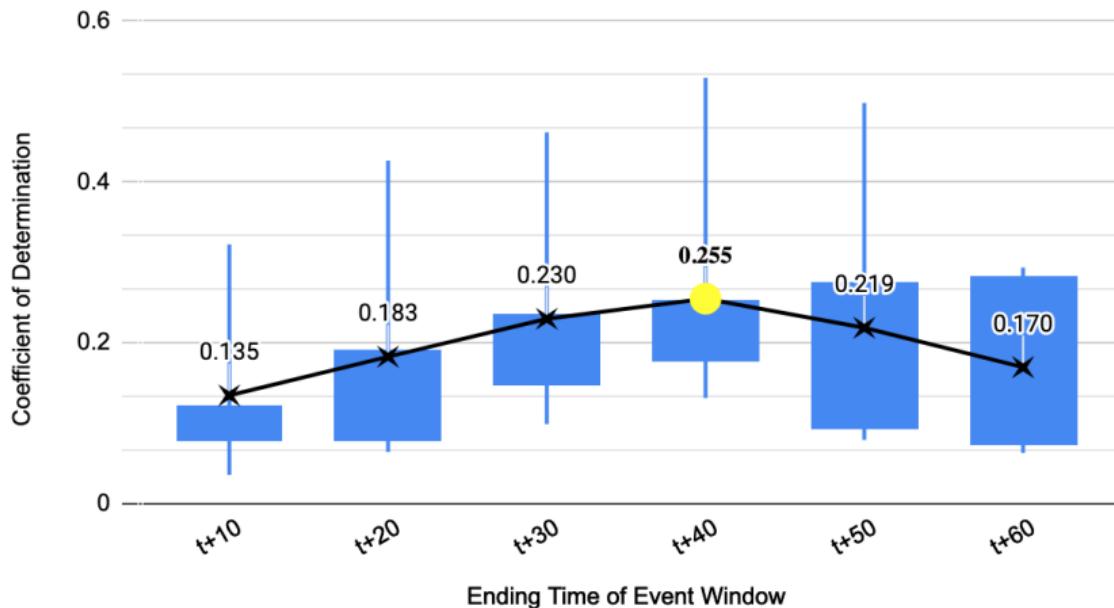
Out-of-sample R<sup>2</sup> for FF4 (Averaged Across Splits)



# Optimal Event Windows: *EDcm2*

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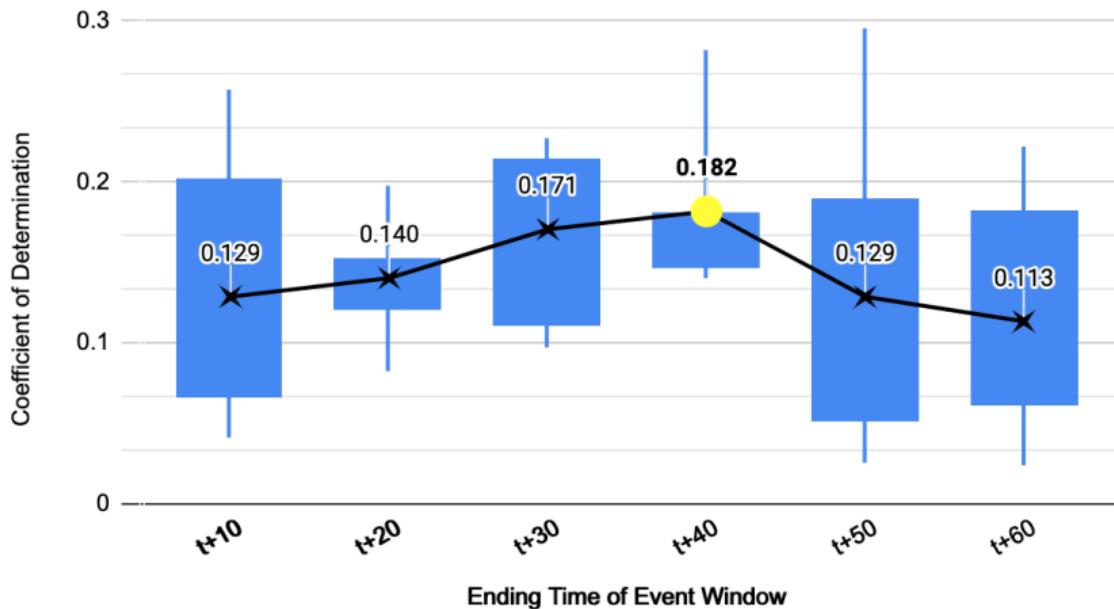
Out-of-sample R<sup>2</sup> for EDcm2 (Averaged Across Splits)



# Optimal Event Windows: *EDcm3*

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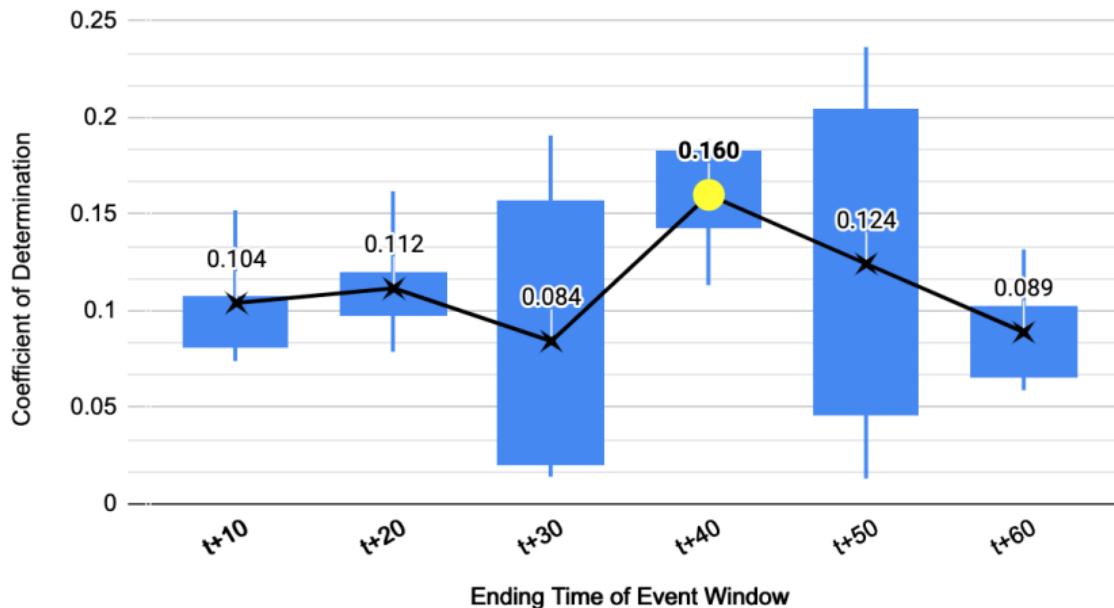
Out-of-sample R<sup>2</sup> for EDcm3 (Averaged Across Splits)



# Optimal Event Windows: *EDcm4*

[Back to Summary Text](#)

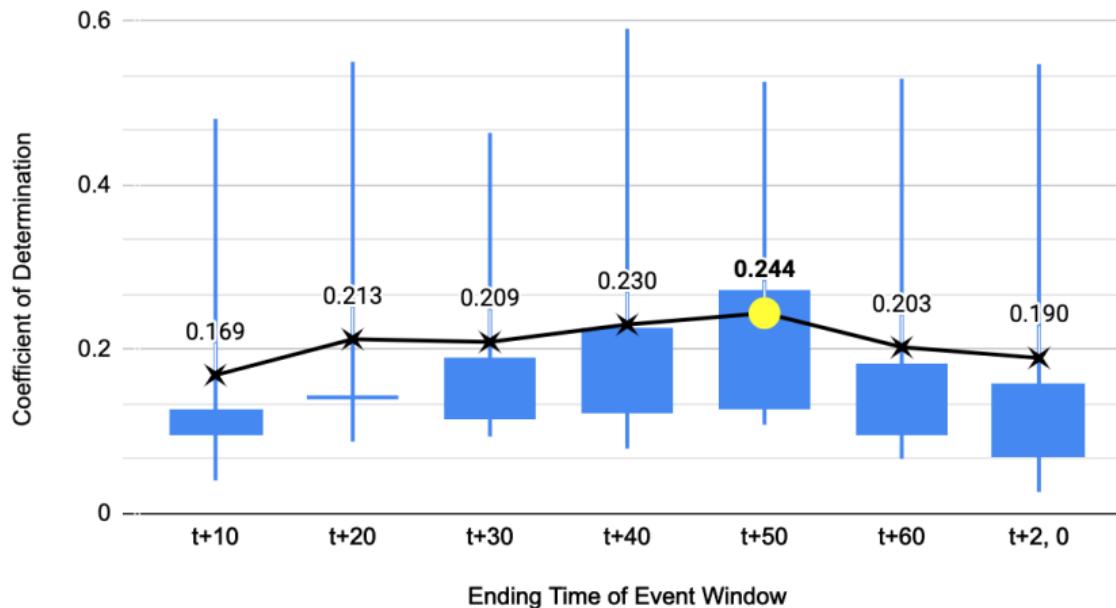
Out-of-sample R<sup>2</sup> for EDcm4 (Averaged Across Splits)



# Optimal Event Windows: TUC1

[Back to Summary Text](#) [One Signal](#)

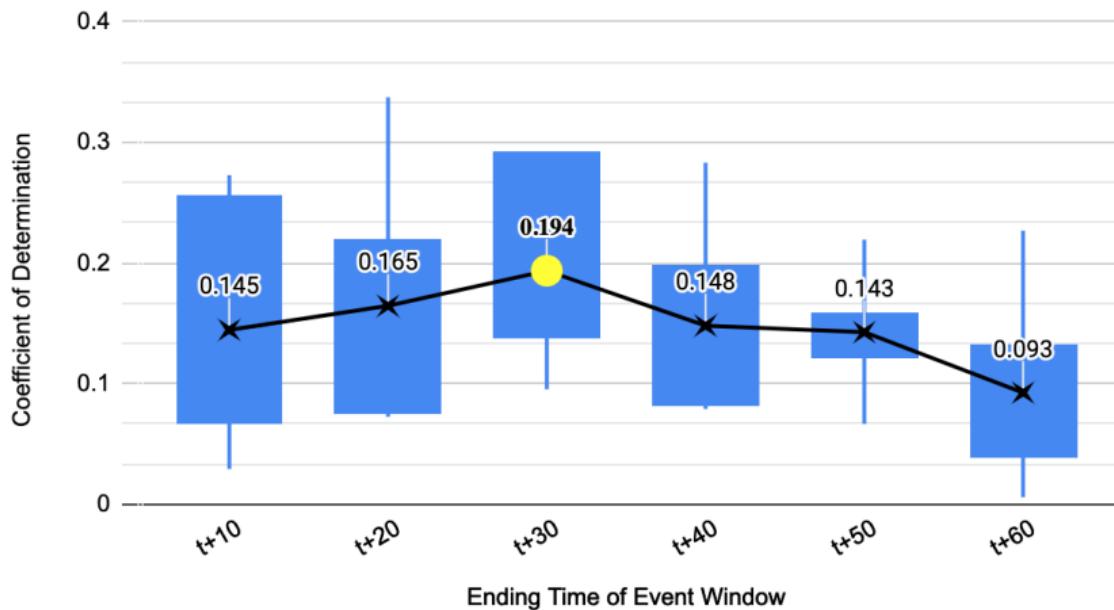
Out-of-sample R<sup>2</sup> for TUC1 (Averaged Across Splits)



# Optimal Event Windows: *TUc2*

[Back to Summary Text](#)

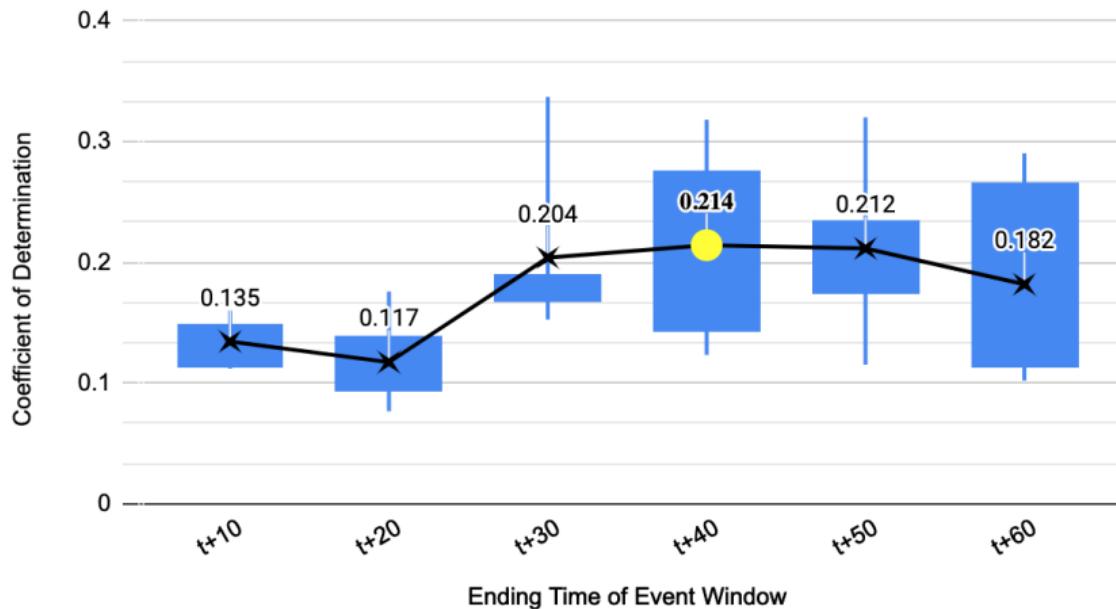
Out-of-sample R<sup>2</sup> for TUc2 (Averaged Across Splits)



# Optimal Event Windows: $FVc1$

[Back to Summary Text](#)

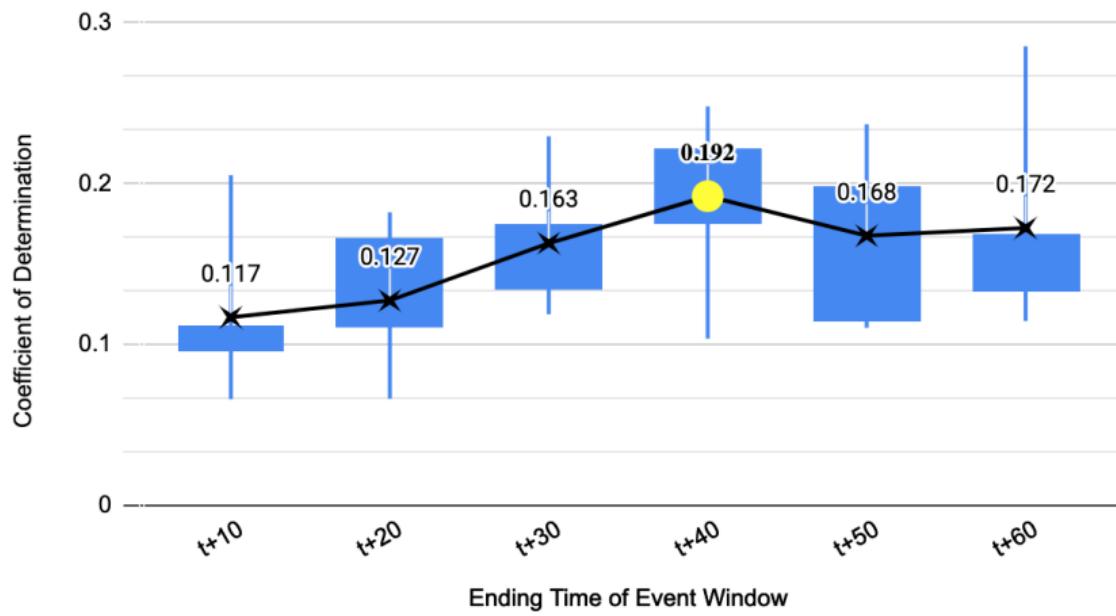
Out-of-sample  $R^2$  for  $FVc1$  (Averaged Across Splits)



# Optimal Event Windows: $FVc2$

[Back to Summary Text](#)

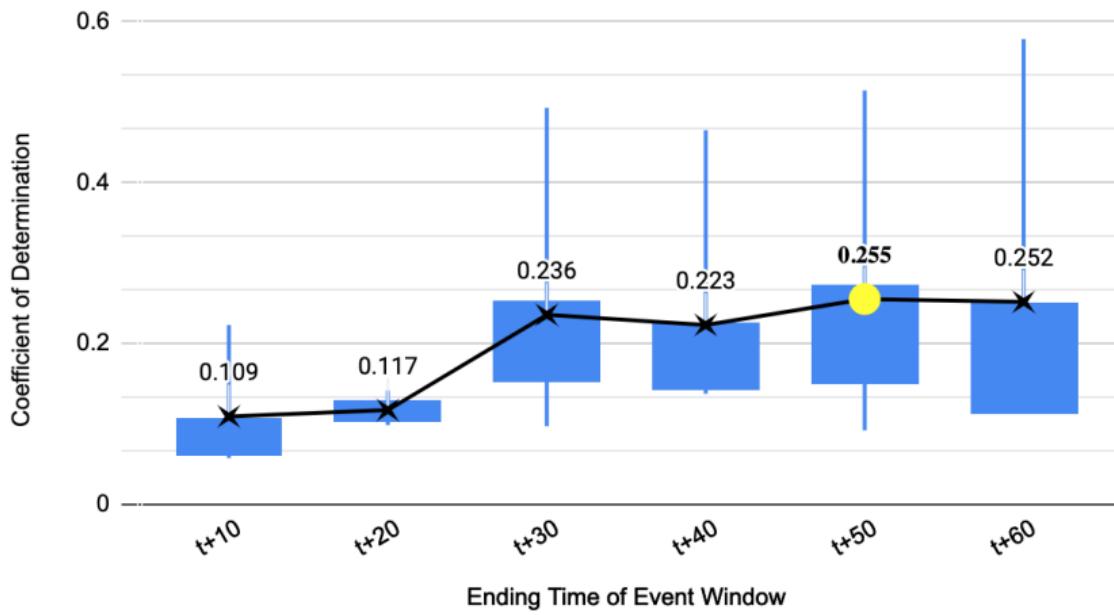
Out-of-sample  $R^2$  for  $FVc2$  (Averaged Across Splits)



# Optimal Event Windows: TYc1

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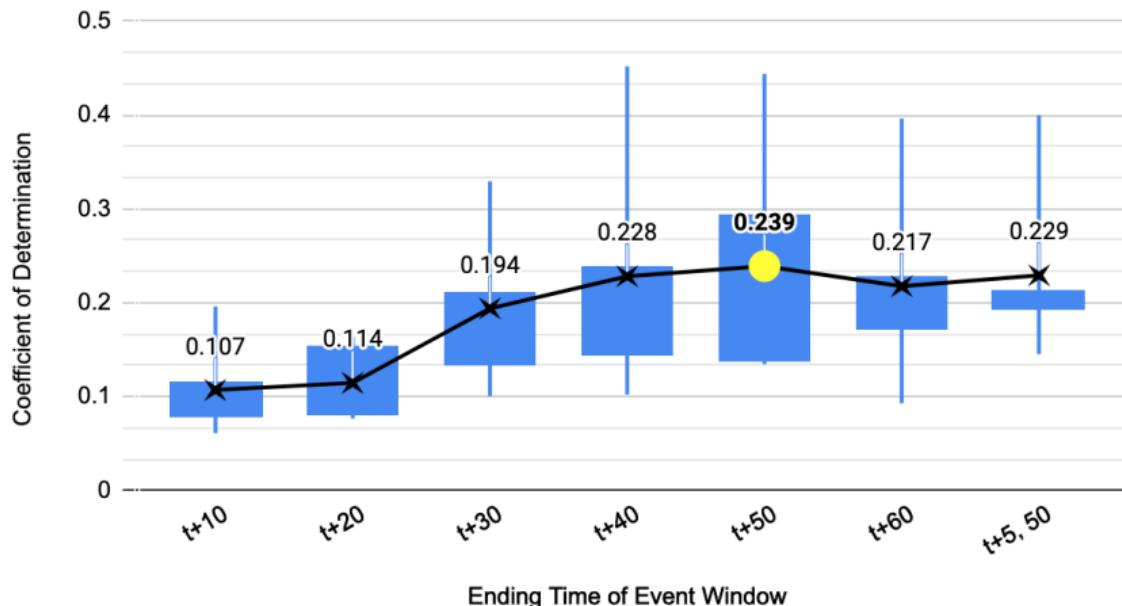
Out-of-sample R<sup>2</sup> for TYc1 (Averaged Across Splits)



# Estimating Optimal Event Windows: TYc2

[Back to Summary Text](#) [One Signal](#)

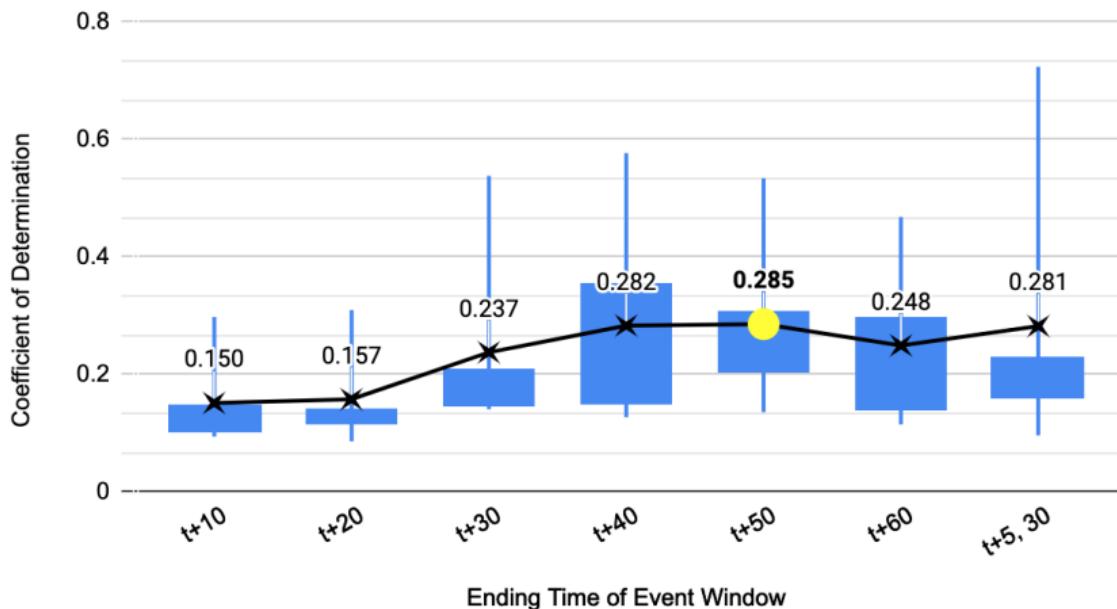
Out-of-sample R<sup>2</sup> for TYc2 (Averaged Across Splits)



# Optimal Event Windows: USc1

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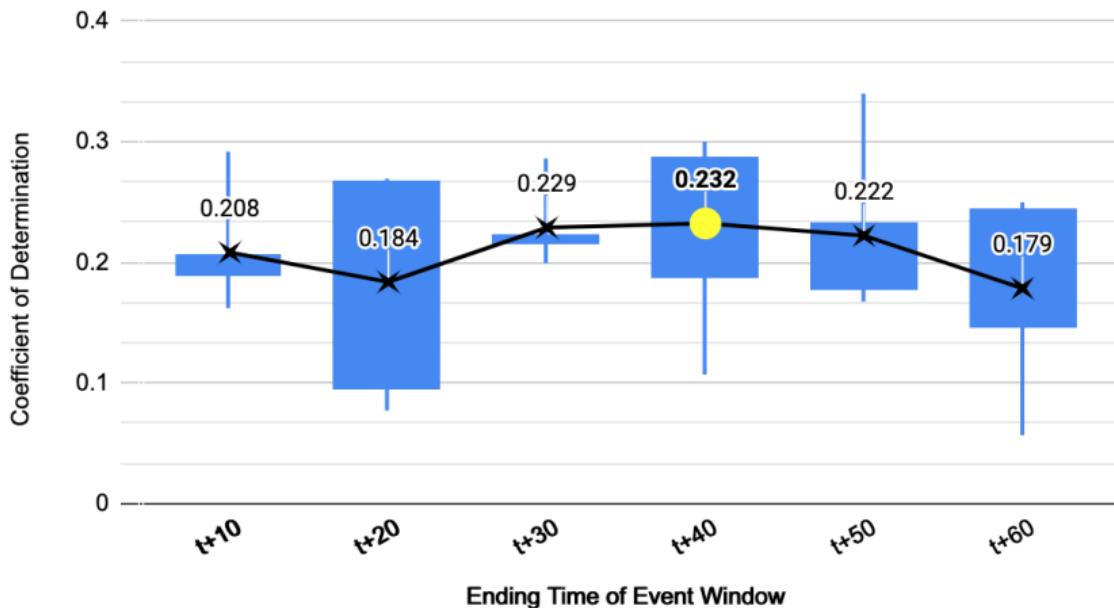
Out-of-sample R<sup>2</sup> for USc1 (Averaged Across Splits)



# Optimal Event Windows: SPX

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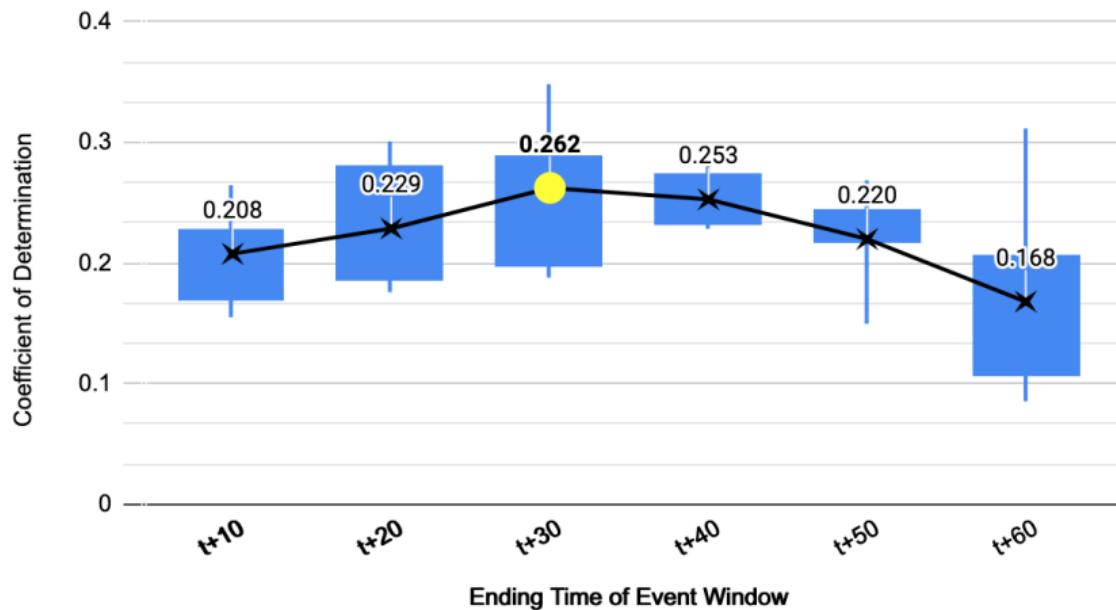
Out-of-sample R<sup>2</sup> for SPX (Averaged Across Splits)



# Optimal Event Windows: ESc1

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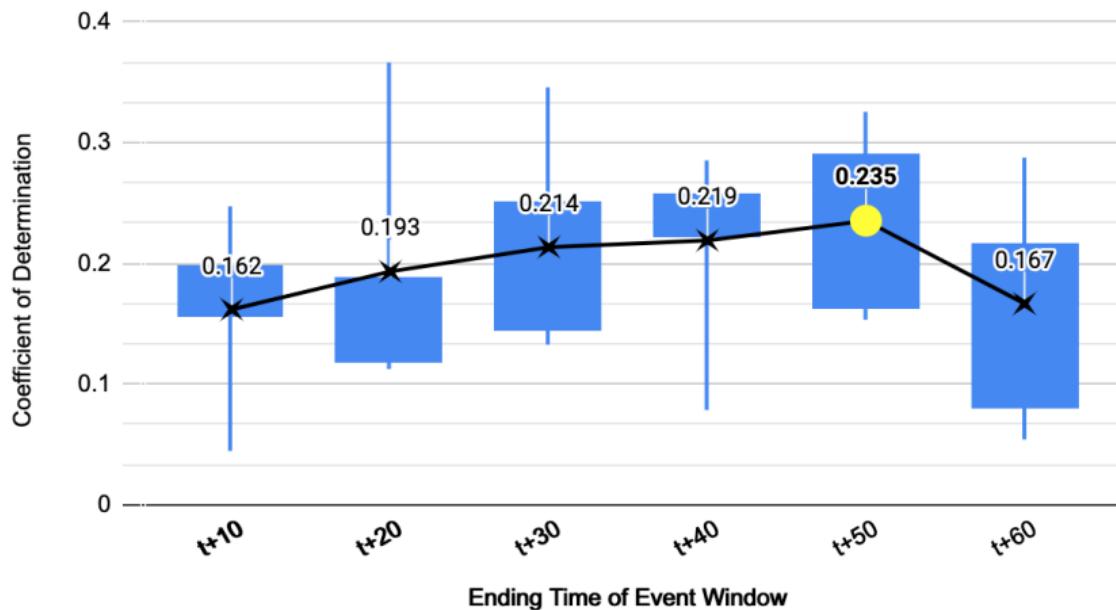
Out-of-sample R<sup>2</sup> for ESc1 (Averaged Across Splits)



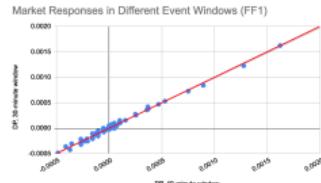
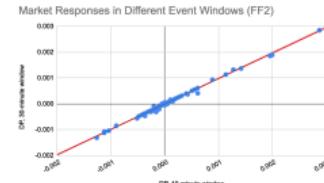
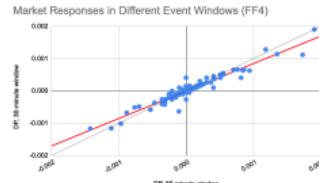
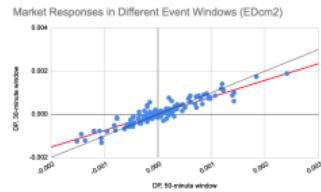
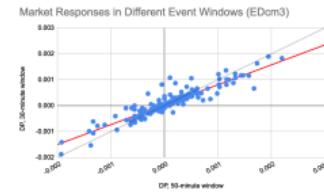
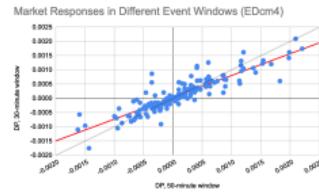
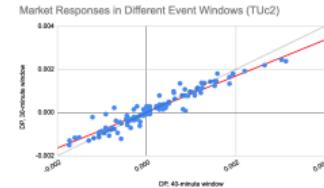
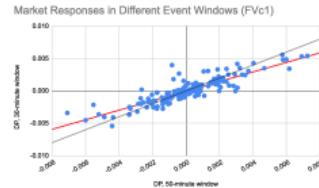
# Optimal Event Windows: *ESc2*

[Back to Summary Text](#)

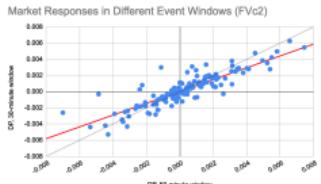
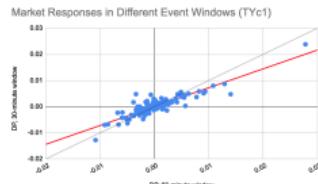
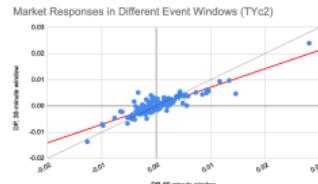
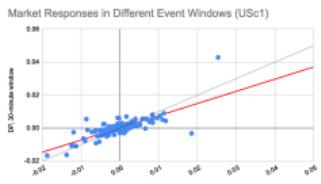
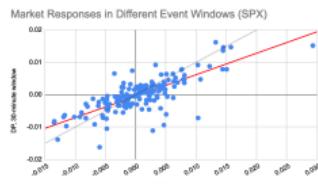
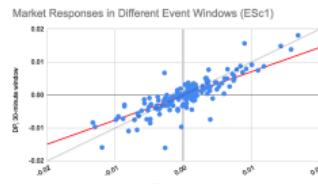
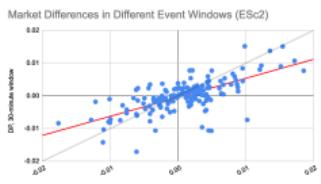
Out-of-sample R<sup>2</sup> for ESc2 (Averaged Across Splits)



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

(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)

(a) *FVc2\*\*\**(b) *TYc1\*\*\**(c) *TYc2\*\*\**(d) *USc1\*\*\**(e) *SPX\*\*\**(f) *ESc1\*\*\**(g) *ESc2\*\*\**

# Interest-rate Futures Prices into MP Surprises: $mp1$

[Back to MP surprises](#)

- ▶ For given expiry month, FFF pays out, on last day,  $100 - \text{avg FFR}$
- ▶ Price of  $(1-j)$  month-ahead FFF at time  $t$  for FOMC meeting  $\tau$ :  $p_{\tau,t}^{FFj}$
- ▶ Expected avg FFR at  $t$  for  $\tau$ :  $FFj_{\tau,t} = 100 - p_{\tau,t}^{FFj}$
- Current-meeting FFR surprise  $mp1_{\tau,t+n}$ :

$$mp1_{\tau,t+n} = \frac{m}{m-d} (FF1_{\tau,t+n} - FF1_{\tau,t-10}), \quad (11)$$

- ▶ 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  $mp2_{\tau, t+n}$ :

$$mp2_{\tau, t+n} = \frac{m_2}{m_2 - d_2} \left\{ [FFj_{\tau, t+n} - FFj_{\tau, t-10}] - \frac{d_2}{m_2} mp1_{\tau, t+n} \right\}, \quad (12)$$

- ▶ 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: $\Delta edj$

[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  $\tau$ :  $p_{\tau,t}^{edj}$
- ▶ Implied rate at  $t$  for  $\tau$ :  $edj_{\tau,t} = 100 - p_{\tau,t}^{edj}$
- Implied rate surprise  $j$ -quarters out  $edj_{\tau,t+n}$ :

$$edj_{\tau,t+n} = edj_{\tau,t+n} - edj_{\tau,t-10}, \quad (13)$$

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

# Interest-rate Futures Prices into MP Surprises: $\Delta tk$

[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  $\tau$ :  $p_{\tau,t}^{tk^j}$
- Implied yield surprise for meeting  $\tau$   $tk_{\tau,t+n}$ :

$$tk_{\tau,t+n} = - \left( p_{\tau,t+n}^{tk^j} - p_{\tau,t-10}^{tk^j} \right) / I, \quad (14)$$

- ▶ If  $\tau \in \{\text{Mar, Jun, Sep, Dec}\} \implies tk_{\tau,t+n} = - \left( p_{\tau,t+n}^{tk^{j+1}} - p_{\tau,t-10}^{tk^{j+1}} \right) / I$
- ▶ Approximated maturities  $I \in \{2, 4, 7, 15\}$  by Gürkaynak, Kisacikoglu, 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:  $\underbrace{PC1}_{N \times 1} = \underbrace{X}_{N \times 2} \cdot \underbrace{V}_{2 \times 1},$ 
  1.  $X$  = Covariance matrix of variables
  2.  $V$  = Eigenvector of covariance matrix  $X$  that has largest eigenvalue
- ▶ Largest eigenvalue → Captures most common variation in data
- Corresponding eigenvector is “direction” explaining data variation

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

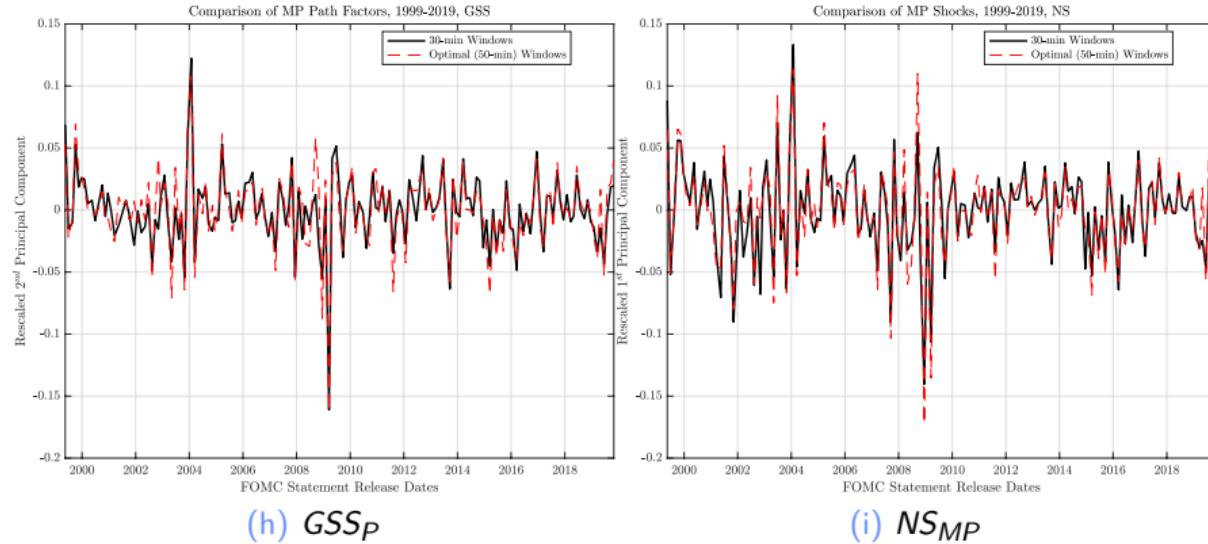
[Back to MP Shocks](#)

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

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

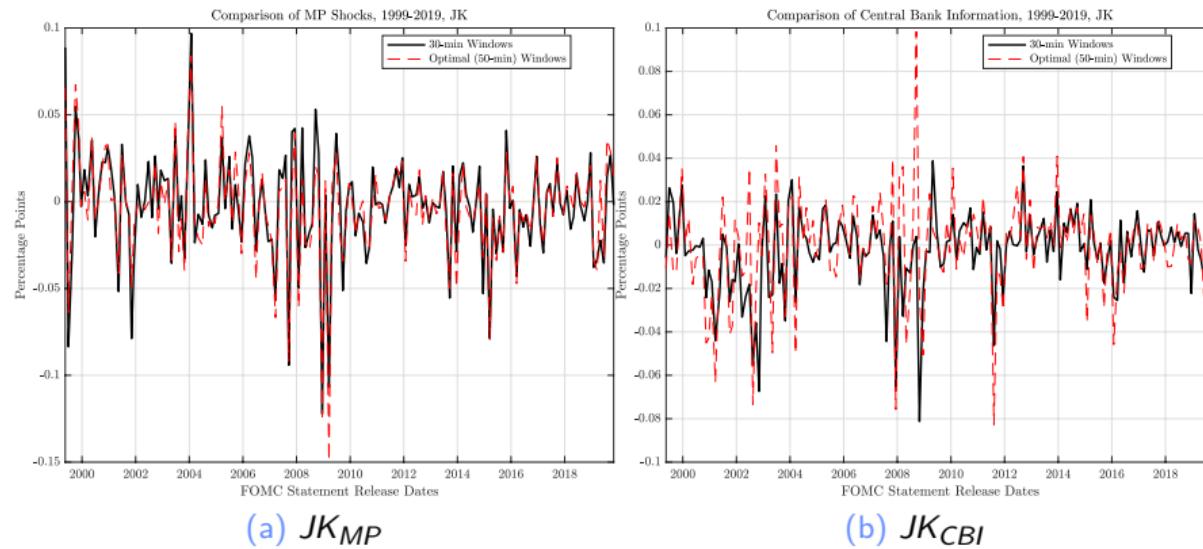
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Figure 2: Comparing Monetary Policy Shock Series Derived from Optimal Window Length v. 30 Minutes

# Monetary Policy Shocks: 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	-0.0024	-0.0030
	(0)	(0)	(0)	(-0.0036)	(-0.0003)
SD	0.0341	0.0280	0.0276	0.0317	0.0197
	(0.0381)	(0.0248)	(0.0286)	(0.0301)	(0.0216)
Max	0.1275	0.0966	0.1197	0.1005	0.0423
	(0.1153)	(0.0750)	(0.1000)	(0.0852)	(0.0914)
$75^{th}$	0.0184	0.0097	0.0131	0.0182	0.0075
	(0.0206)	(0.0097)	(0.0155)	(0.0126)	(0.0104)
Median	0.0031	0.0015	-0.0010	-0.0018	-0.0003
	(0.0024)	(0.0022)	(0.0003)	(-0.0009)	(0.0021)
$25^{th}$	-0.0179	-0.0088	-0.0122	-0.0158	-0.0094
	(-0.0167)	(-0.0088)	(-0.0118)	(-0.0140)	(-0.0095)
Min	-0.1343	-0.1327	-0.1576	-0.1268	-0.0887
	(-0.1750)	(-0.1179)	(-0.1500)	(-0.1512)	(-0.0769)

Table 13: Descriptive Statistics for Monetary Policy Shock Series

# 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<sup>||</sup>
  - No: Go back to step 1

---

<sup>||</sup>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<sup>||</sup>
  - No: Go back to step 1

## ► Results:

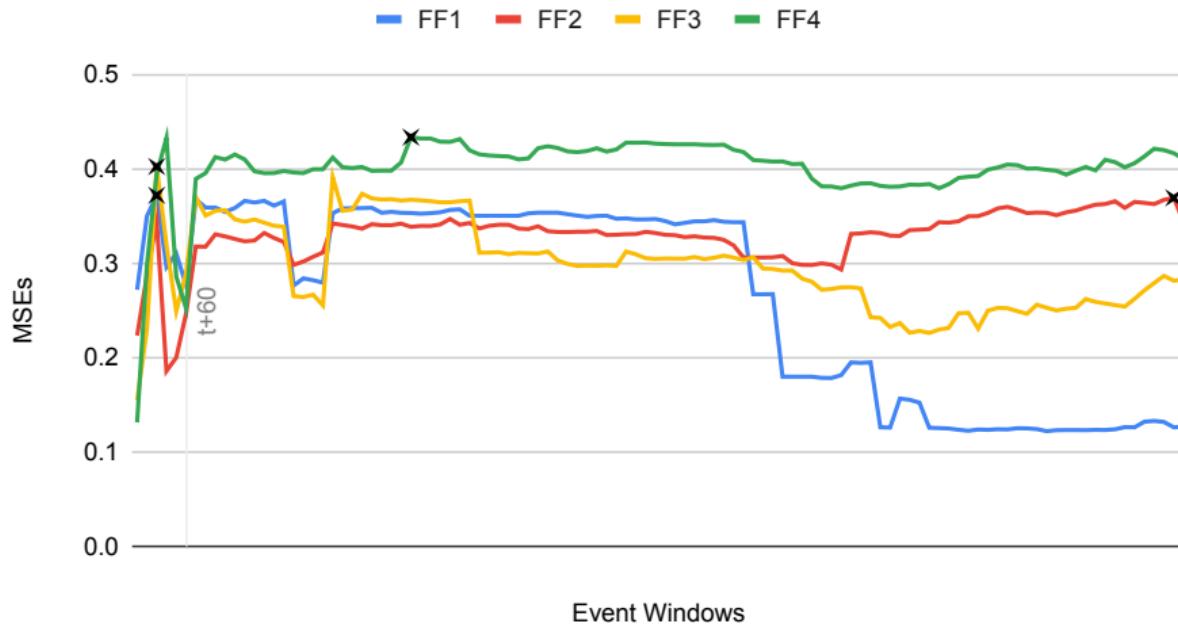
1. Optimal window length has highest  $\overline{R^2_{OOS}}$
2. “Jointly” estimated  $\overline{R^2_{OOS}}$  for window  $> t + 60$  greater than “” for window  $t + 20$ 
  - Event window with global maximum  $\overline{R^2_{OOS}}$  could be in window length  $> t + 60$

<sup>||</sup>Performed for *FF2, FF4, TUc1, TYc2, USc1*.

# Testing $R^2$ Using “One Signal” Approach for Federal Funds Futures

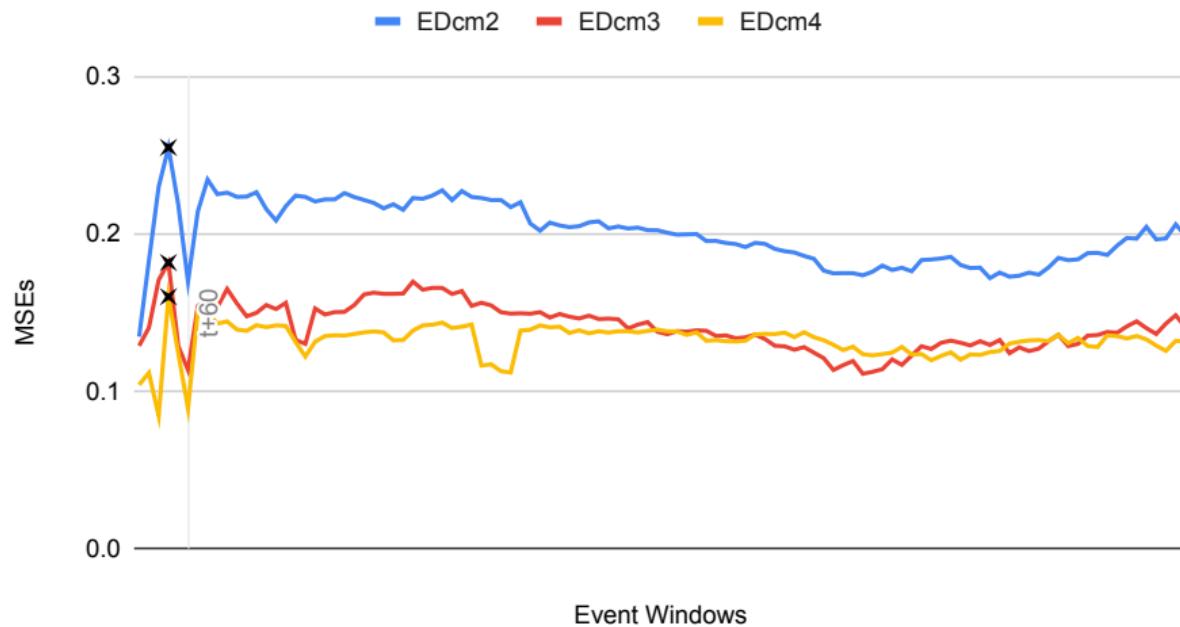
FF2 FF4

## Out-of-sample $R^2$ Using "One Signal" Approach (FFFs)



# Testing $R^2$ Using “One Signal” Approach for Eurodollar Futures

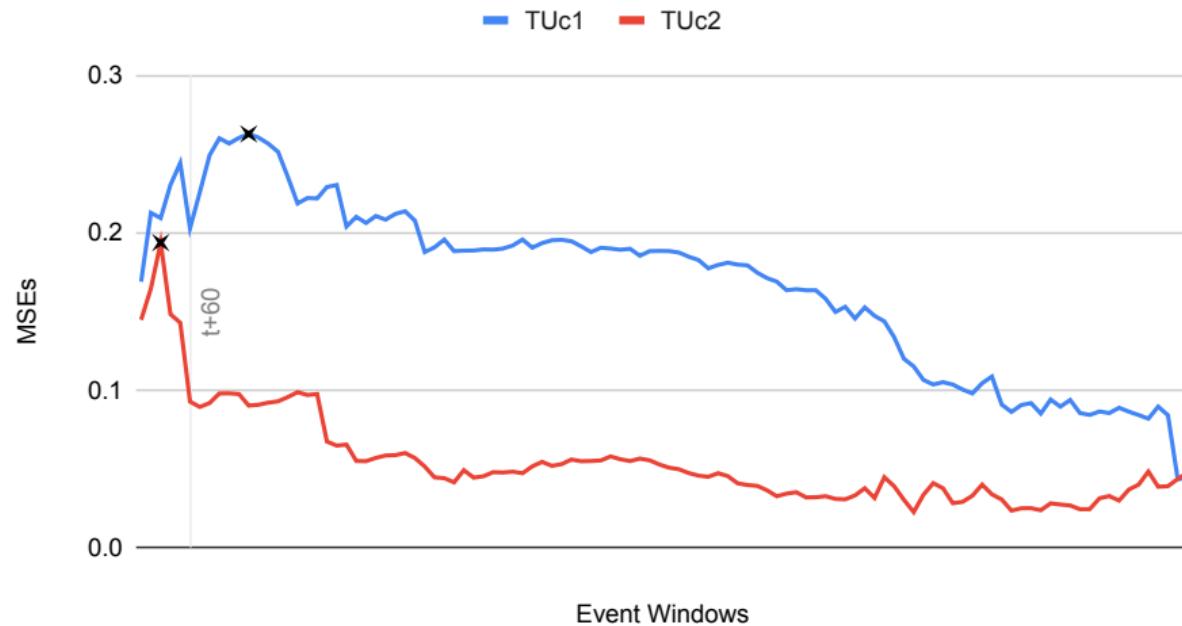
## Out-of-sample $R^2$ Using "One Signal" Approach (EDs)



# Testing $R^2$ Using “One Signal” Approach for 2-Year Treasury Futures

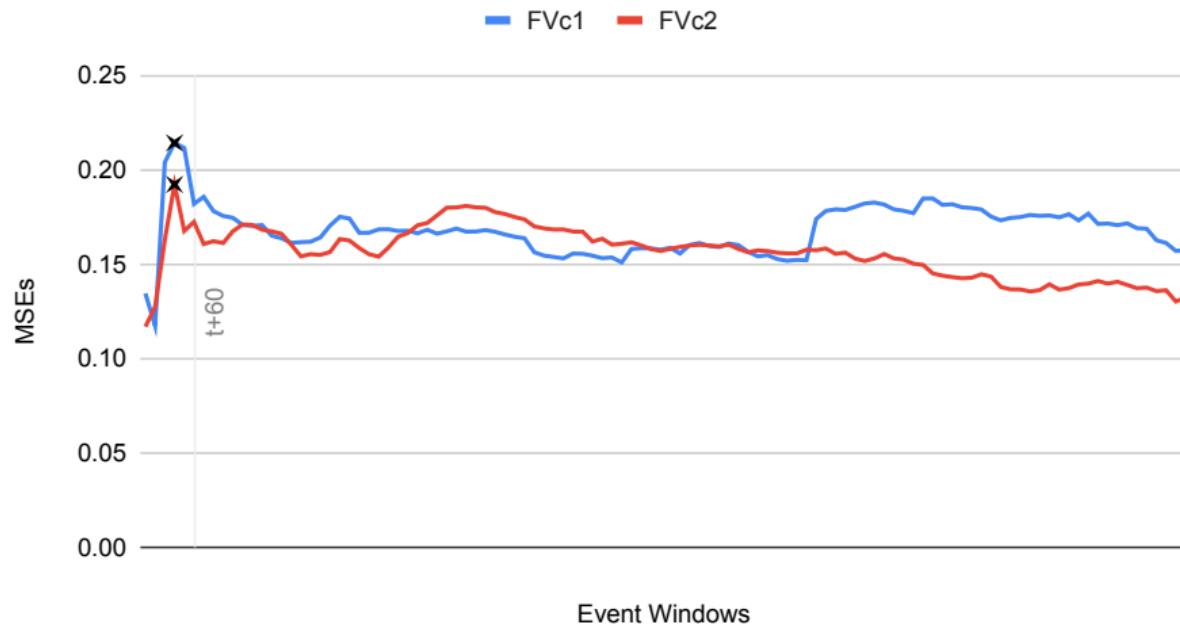
TUc1

Out-of-sample  $R^2$  Using "One Signal" Approach (TUs)



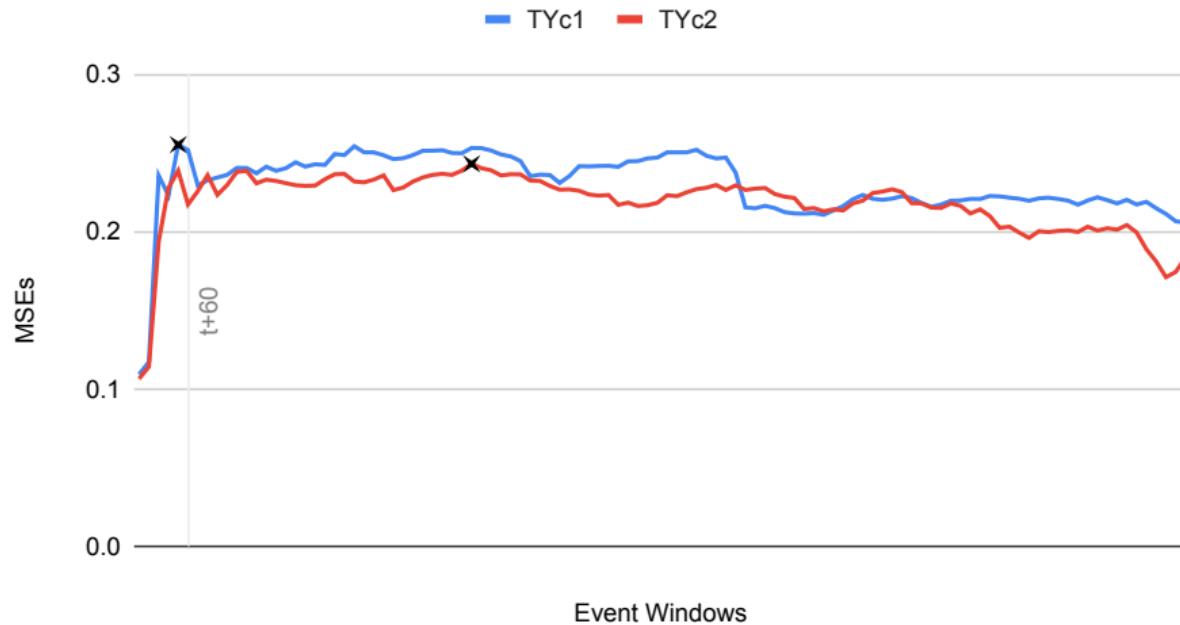
# Testing $R^2$ Using “One Signal” Approach for 5-Year Treasury Futures

## Out-of-sample $R^2$ Using "One Signal" Approach (FVs)



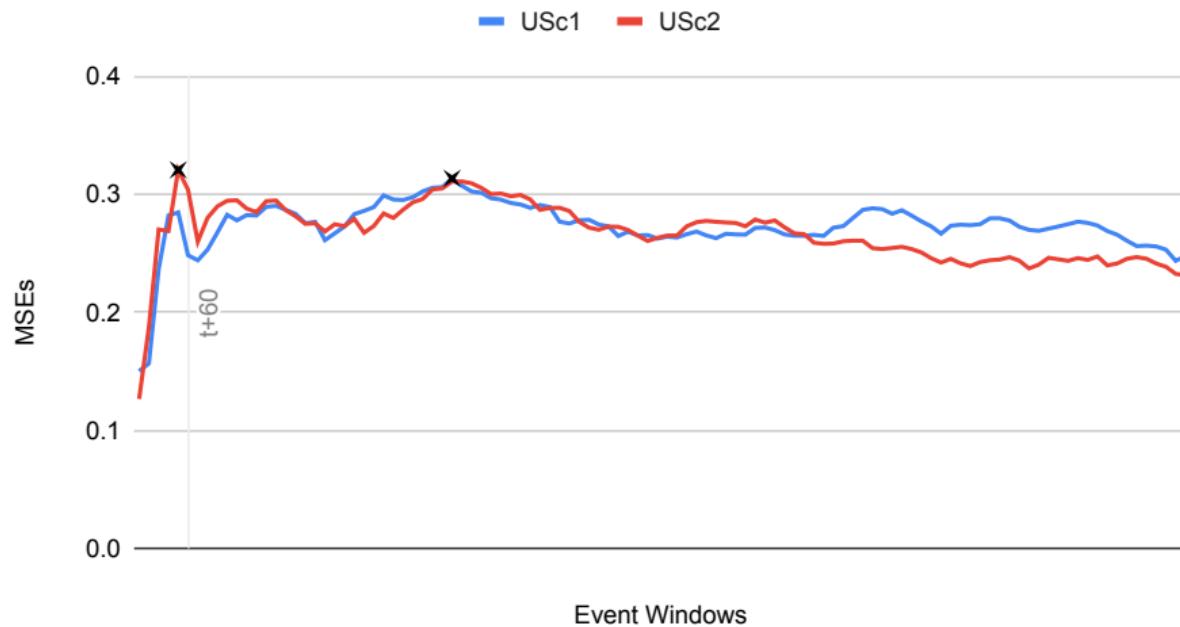
# Testing $R^2$ Using “One Signal” Approach for 10-Year Treasury Futures TYc2

## Out-of-sample $R^2$ Using "One Signal" Approach (TYs)



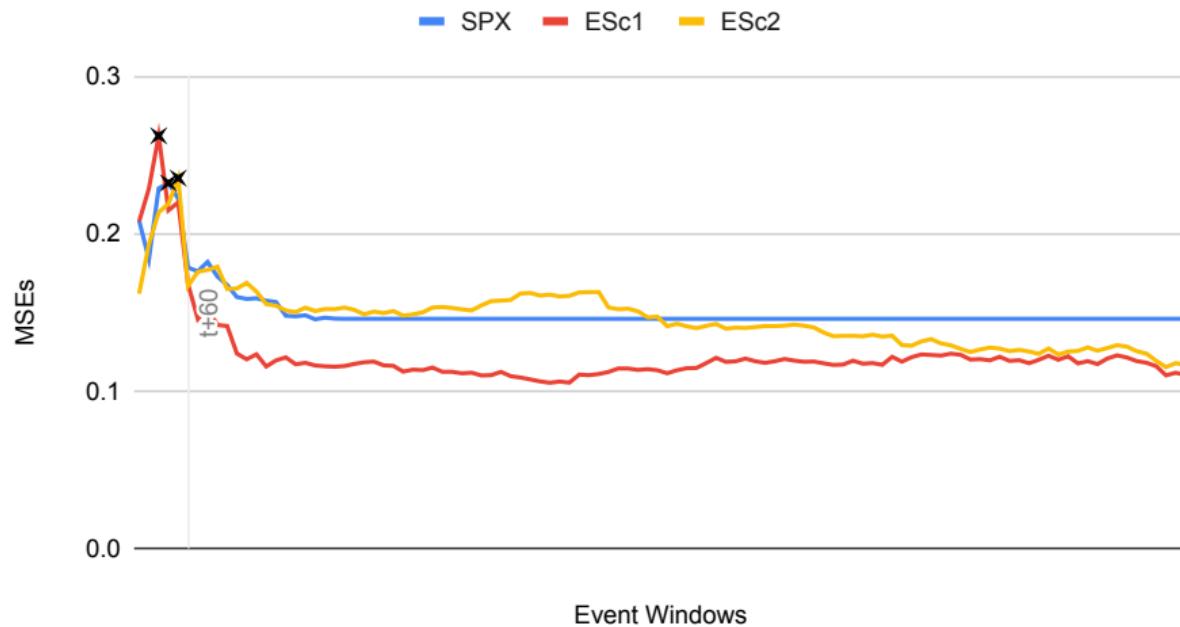
# Testing $R^2$ Using “One Signal” Approach for 30-Year Treasury Futures USc1

## Out-of-sample $R^2$ Using "One Signal" Approach (USs)



# Testing $R^2$ Using “One Signal” Approach for S&P Index

## Out-of-sample $R^2$ Using "One Signal" Approach (S&P 500)



# TFIDF Equation

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

- ▶  $tf_{d,t}$ : 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

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- ▶ 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

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- ▶ 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 14: FOMC Statement Base Terms with Top 30 TFIDF Scores

# Cosine Similarity Matrix

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