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

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Abstract

This paper shows that financial markets need more time to fully react to Federal Open Market Committee (FOMC) policy announcements than typically assumed. Using finance literature techniques and neural network methods for text analysis, I systematically estimate the event window lengths that best reflect market full reactions to only the information content of FOMC statements. On average, markets fully react within an event window *ending at least 30 minutes* after release. This optimal window increases with asset time horizon, reaching 50–60 minutes for maturities at least two quarters ahead, showing that a single window length does not fit all asset types. Additionally, statements with greater complexity, less similarity, and the presence of dissents are associated with longer event windows on average. The choice of event window has economically meaningful consequences; the correlation between monetary policy surprises measured within optimal versus conventional 30-minute windows decreases with asset time horizon. These differences alter the forward guidance component of monetary policy shocks and magnify their estimated impact on interest rates and equity prices.

Keywords: Event window studies, FOMC statements, monetary policy shocks, neural networks, natural language processing, text analysis

JEL Codes: C45, E52, E58, G14

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1 Introduction

> To establish the right price for a stock the market must have adequate information, but it by no means follows that if the market has this information it will thereupon establish the right price. The market's evaluation of the same data can vary over a wide range, dependent on bullish enthusiasm, concentrated speculative interest and similar influence, or bearish disillusionment. Knowledge is only one ingredient on arriving at a stock's proper price. The other ingredient, fully as important is sound judgement.
>
> Graham (1974)

How much time do financial markets need to fully respond to news? The answer might not be obvious. Consider the following example of the S&P 500 Index price movement shortly after the release of the January 2008 Federal Open Market Committee (FOMC) monetary policy announcement. As shown in Figure 1, measuring the price change up to different times after the announcement leads to different conclusions on how positive was the reaction of the stock market index. In other words, the *time window* chosen to measure financial market price reactions to news can change the answer to the original question.

Because changes in financial prices can serve as proxy for changes in market expectations, applied macroeconomists have used tools such as event window studies to measure the unanticipated financial market response to news and capture the predicted effect of events on macroeconomic outcomes. However, news releases can be dense and difficult to interpret, especially when the information content deals with longer time horizons. As a result, whilst markets may need more than a few minutes to react to complex events or policy announcements, longer windows increase the likelihood that the measurement will be contaminated as additional news is revealed, making it difficult to assign market price responses to a particular event. Balancing these two forces is what allows the field to pin down the event window length that should be used to determine the response of financial markets to news releases. Therefore, determining the optimal window length is an empirical question and not a parameter whose value we should simply assume.

A relevant and important application of event window studies is to construct monetary policy surprises, which are unanticipated changes in interest rates around the FOMC policy announcements. Monetary policy surprises can be used directly (e.g., Kuttner, 2001; Gürkaynak, Sack, and Swanson, 2005; and others) or used as an instrument in a structural vector autoregressive or local projections framework (e.g., Gertler and Karadi, 2015; Jarociński and Karadi, 2020; Handlan, 2022b; Piller et al. (2025); and others) to estimate the effects of monetary policy shocks on asset prices and the macroeconomy.

The choice of event window size for monetary policy surprises in the literature falls into two categories: Short or long window lengths. Proponents of narrow windows around FOMC announcements (e.g., 30 minutes) argue that this high-frequency identification makes plausible the assumption that observed price changes are caused solely by the policy announcement. This approach and the choice of 30-minute windows have become the popular choice and de facto standard in the literature (Gürkaynak, Sack, and Swanson, 2005; Gertler and Karadi, 2015; Nakamura and Steinsson, 2018; Gürkaynak, Kisacikoğlu, et al., 2020; Handlan, 2022b; Swanson and Jayawickrema, 2023; Bauer and Swanson, 2023; and others). An implicit assumption from this argument is that the initial price reaction of financial markets within small event windows is equal to the full reaction. However, this implicit assumption could be violated due to various issues potentially facing financial markets, such as over-reactions (e.g., Boguth et al., 2023; Bianchi et al., 2024), under-reactions (e.g., Boguth et al., 2023; Bianchi et al., 2024), the presence of noise trading (e.g., Hervé et al., 2019; Ben-David et al., 2022), and algorithmic trading (e.g., Bazzana and Collini, 2020; Ben Ammar and Hellara, 2022). In addition, Ramey (2016) finds that the macroeconomic effects of monetary policy surprises constructed with samples beginning after 1984 declined in precision likely because of how monetary policy was conducted more systematically after this time period. As a result, Ramey (2016) argues that monetary policy shocks now consist mostly of information effects from the FOMC and *noise*. The combination of all these effects could result in monetary policy surprises to lack relevance and precision.

Conversely, those who utilise longer event windows (e.g., 1-hour to 1-day) contend that this approach has a higher probability of capturing the market's full reaction to FOMC announcements, resulting in shock measures constructed from the monetary policy surprises that have higher explanatory power (Kuttner, 2001; Rigobon and Sack, 2004; Gürkaynak, Sack, and Swanson, 2005; Gürkaynak, Kisacikoğlu, et al., 2020; Bauer, Lakdawala, et al., 2022; Swanson and Jayawickrema, 2023; Boehm and Kroner, 2025b; An et al. (2025); Boehm and Kroner (2025a); and others). Unfortunately, the trade-off with this alternative size is that longer event window lengths increase the chance that measurements are contaminated with unrelated news, causing a decline in statistical significance and precision of estimates (e.g., Gürkaynak, Sack, and Swanson, 2005; Nakamura and Steinsson, 2018).

Ultimately, the choice of event window length has remained an "ad-hoc" decision. Relatedly, the literature has implicitly assumed that this choice applies to all assets, an assumption that may not hold. For example, markets for assets with short time horizons might price in FOMC policy announcements more easily, whilst markets for assets with longer time horizons might need more time.[1] Therefore, one might expect that longer event window lengths are required to capture the full reaction of the markets for assets such as longer-term bonds and equities.

The observed trade-offs with different event window sizes bring up a crucial question: how does one choose the appropriate event window length for their study in monetary policy? For a literature that has available a fininite sample of policy announcements, the wrong answer to this question could result in monetary policy surprises whose effects are either attenuated with classical measurement error or possess confounding factors.

For a methodology as widespread as event window studies in empirical macroeconomics and finance, there are surprisingly very few papers that directly investigate the appropriate length of time over which to measure price reactions in either literature. One of the earliest papers looking into this question was Hillmer and Yu (1979), who develop a theory around the assumption that there exist two price reaction processes: One during a period of ad-

[1] Throughout this paper, I differentiate between "time horizon" and "futures contract maturity". The former typically refers to the maturity of the underlying asset for futures contracts (e.g., 2-year Treasury futures deal with interest rate expectations 2 years into the future). The latter refers to the expiration date of the futures contract themselves, (e.g., front-month 2-year Treasury futures).

justment to the event of interest and one outside the reaction period. Tests of their model show that as long as markets are still reacting to the new information, the variance of the price reactions within the event window was higher than in periods outside of the window. Using intraday data, the authors find that the event window should last several hours after the initial event of interest. Chang and Chen (1989) apply the methodology of Hillmer and Yu (1979) on daily data, finding that event windows should span several days due to the market continuing to react to the initial event. Krivin et al. (2003) propose various proxy rules for determining the length when looking at a limited number of observations, such as those based on significant abnormal returns. The authors find that rules based on continuing price movements result in event window sizes that correlate with the "size" of the news. Das and King (2021) attempt to provide some systematic structure by measuring the informativeness of earnings announcements using abnormal R^2 and other statistics, discovering that asymmetric, narrower one-day event windows exhibit greater information content. A recent paper by Boehm and Kroner (2025a) combines the equivalent of a one-step Kalman filter estimation with the heteroscedasticity-based approach of Rigobon and Sack (2004) to identify the event window around FOMC announcements where excess variance is no longer statistically significant. Under this criterion, the authors select an event window length of fourteen hours.

My paper builds upon this literature from an alternative angle. Whilst the aforementioned studies infer the optimal window length using only observed price dynamics, my approach combines these price dynamics with a text-based signal of the market's price response under the minimised impact of noise to further pin down the optimal window length. In particular, I use neural network methods for text analysis to approximate the underlying relationship between the information content of FOMC statements to the market price response. The signal comes from this approximation and represents the predicted price reaction of the market to the monetary policy announcement, word-for-word. Using this text-based signal, I am then able to estimate the optimal event window length that best reflects the *full* price reaction of the market to the FOMC statement, an interpretation of the signal that is only possible when the impact of noise is *minimised* on average within this window length. My method provides an explicit and systematic approach for setting this basic step in event window studies for the high-frequency identification literature and a deeper discussion into the effects of event window choice on empirically measured monetary policy surprises and shocks.

This method yields four key findings: first, in line with the insights from Hillmer and Yu (1979) and Boehm and Kroner (2025a), my results show that financial markets take more time to process news than is typically assumed in modern high-frequency identification studies. Specifically, I find that regardless of contract maturity, financial markets for futures and equities fully react to the information content of FOMC statements within an event window starting 10 minutes before and *ending at least 30 minutes* after release. In other words, I show that the time financial markets need to fully react to FOMC policy announcements is longer than what is popularly assumed in the literature. Second, and unlike those earlier papers, I find the optimal window length varies systematically across asset classes and maturities. Figure 2 offers a stylised summary of the main results. It displays the systematically estimated event window lengths from my method for all considered asset time horizons, such as 2-year Treasury futures, which contain information about the market expectations on interest rate expectations and risk premia about 2 years ahead. As mentioned above, markets for assets with the shortest time horizons are estimated to fully react within a 40-minute event window. As the maturity increases, the window length rises accordingly, levelling off at an event window beginning 10 minutes before and ending 40–50 minutes after statement release. In other words, my paper documents that the optimal event window length varies across asset types and time horizon in a systematic way. Relatedly, I document that statements with greater complexity, less similarity, and the presence of dissents have relatively longer event windows on average. Third, I document that the correlation between monetary policy surprises constructed within optimally-found event window lengths v. the popular 30-

minute window decreases for all time horizons when increasing the optimal window length. Furthermore, increasing the time horizons of the surprises also sees the correlation fall by a larger magnitude under longer optimal window lengths. Whilst interest-rate surprises for current and next FOMC meetings are similar regardless of event window choice, the differences result in a decline in the correlation by 10% for surprises dealing with fifteen years out. I find that these differences in the surprises affect monetary policy shocks about forward guidance in a variety of ways, such as larger magnitude in the peaks and troughs of the shocks or "shifts in importance" of shock compositions. Fourth, opening up the window from the popular 30 minutes to the optimal length causes the responses of interest rates and equity prices on monetary policy shocks about forward guidance to become larger. As a result, previously documented effects of monetary policy shocks could be attenuated from the usage of suboptimal window lengths.

When it comes to general applications of text analysis methods in economics, most empirical studies have employed the techniques of clustering words into topics or using word counts to fit predictive models (Gentzkow et al., 2019). Many such examples exist in literature that studies the effects of central bank communication through text analysis, such as Acosta (2023) in their measures of expansionary versus contractionary monetary policy sentiment and Husted et al. (2020) in their creation of a monetary policy uncertainty index. These techniques are popular because they allow researchers to choose the interpretation and emphasis of individual words. However, a common disadvantage amongst these methods is that more complex features of text, such as context and word interdependencies, are not captured. In contrast, neural networks for text analysis do not overlook these characteristics, allowing these algorithms to quantify and use the "full" information content of text. Thanks to the techniques of transfer learning and pre-training from the computer science literature, adapting text-analysis neural networks for finite sample applications, such as studying the effects of monetary policy communication on economic outcomes and expectations, has become feasible.

The most similar examples to the approach of my paper that take advantage of these neural network methods are Handlan (2022b), Doh et al. (2023), and Piller et al. (2025). Doh et al. (2023) uses an artificial neural network for text analysis called the Universal Sentence Encoder to measure differences in hawkish-dovish sentiment between official and alternative FOMC statements and create a stance metric over time. Handlan (2022b) approaches these same types of monetary policy statements with a different text-analysis neural network, XLNet-Base from Yang et al. (2019), to create monetary policy text shocks. With this combination, she is able to remove the "Fed Information Effect" (Miranda-Agrippino and Ricco, 2021) from the forward guidance component. Impulse responses of macroeconomic variables from her text shock follow the same trends and amplitudes as those predicted by theory. Building from these two studies, Piller et al. (2025) expand the set of FOMC communication considered by XLNet-Base to include Federal Reserve speeches. The result are estimated monetary policy shocks that have stronger relevance and mitigate endogeneity concerns. My paper contributes to this growing literature by utilising the same neural network as in Handlan (2022b) and Piller et al. (2025), but for a first step in the process of obtaining monetary policy shocks: systematic determination of optimal event window lengths around FOMC announcements such that financial markets have fully reacted and are minimally impacted by noise, resulting in more relevant and precise monetary policy surprises (Acosta, 2023).

The remainder of this paper is structured as follows. Section 2 provides a simple, conceptual framework of the dynamics of asset market prices in response to news and motivates the necessity of my method for obtaining the text-based signal used to determine the optimal event window length. Section 3 describes the input and output data of the text analysis method. Section 4 details the process of systematically estimating the optimal event window lengths and the neural network approach behind the method. Section 5 presents the estimated length of time that financial markets need to fully react to monetary policy announcements. Section 6 details the effects of event window choice on monetary policy surprises and shocks. Section 7 details how the complexity, similar, and presence of dissents within the FOMC statements can affect the optimal window lengths. Finally, Section 8 concludes.

2 Conceptual Framework and Simulations

In this section I present a conceptual framework that shows how the dynamics of asset market prices in response to news can have conflicting noise components. With this framework and related simulations, I show how systematic estimation of the optimal event window length can be performed using a signal based on the text of news releases.

Consider the price of one asset market at time t, P_t. Assume that the news is released at the beginning of the time period, $t = 0$. As shown in Equation 1, the asset price is the sum of three components:

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

where P_t^f is the fundamental price component, ε_t^c is cognitive noise, and ε_t^n is unrelated news.

P_t^f represents what asset price "should" be set by the market due to news release, meaning it is assumed that $P_t^f = P^f \in \mathbb{R}$. Furthermore, the fundamental price component does not have the same meaning as the standard definition in the asset pricing literature.

Cognitive noise can be thought of as the collective "market noise" due to market participants only being able to react to so much information in a given amount of time. For aforementioned reasons such as algorithmic and noise trading, potential liquidity constraints, and over- or under-reactions, it is possible that market participants will have incomplete information or noise as well as different beliefs of what the news event means to the price of the asset they are trading in a short amount of time. As time progresses after the news release, the cost of processing and reacting to information will decline for more investors, who will also be able to see each other's price responses and react accordingly. These factors lead to a collective convergence to the fundamental price component. In other words, cognitive noise and its error "decay" over time and converge to zero. The framework reflects this behaviour by representing cognitive noise as the following modified AR(1) process:

$$\varepsilon_t^c = \rho_c \varepsilon_{t-1}^c + e^{-\mathcal{D}t} \nu_t^c,$$

where coefficient $|\rho_c| < 1$, decay term $\mathcal{D} \in \mathbb{R}^+$, and random noise ε_t^c is normally distributed with mean zero and variance σ_c^2. Two necessary assumptions to ensure the cognitive noise process in the framework exhibits the decaying behaviour over time are that $|\frac{\rho_c}{\mathcal{D}}| < 1$ and the variance of cognitive noise at time $t = 0$ is equal to σ_c^2.

The effect of news unrelated to the event of interest on the asset price is modelled as a random walk:

$$\varepsilon_t^n = \varepsilon_{t-1}^n + \nu_t^n,$$

where random noise ν_t^n is normally distributed with mean zero and variance σ_n^2. Similar to cognitive noise, the variance of the unrelated news process at time $t = 0$ is equal to zero.

2.1 The Effects of Noise on the Variance of Asset Prices

The expression of P_t as Equation 1 allows for the derivation of the variance of the asset price for all time $t \geq 0$ through iterative substitution.

At time $t = 0$ when news is released, one can express the variance of the asset price as $\mathrm{Var}(P_0) = \mathrm{Var}(\varepsilon_0^c) + \mathrm{Var}(\varepsilon_0^n) = \sigma_c^2$. Similarly, the expression at time $t = 1$ is $\mathrm{Var}(P_1) = \mathrm{Var}(\varepsilon_1^c) + \mathrm{Var}(\varepsilon_1^n) = \sigma_c^2(\rho_c^2 + e^{-2\mathcal{D}}) + \sigma_n^2$. Continuing this iterative process yields the following expression of

$$\begin{aligned} \mathrm{Var}(P_t | t \geq 0) &= \left[\sum_{i=0}^{t} \rho_c^{2(t-i)} e^{-2\mathcal{D}i} \right] \sigma_c^2 + t\sigma_n^2 \\ &= \left[\frac{\rho_c^{2(t+1)} - e^{-2(t+1)\mathcal{D}}}{\rho_c^2 - e^{-2\mathcal{D}}} \right] \sigma_c^2 + t\sigma_n^2, \end{aligned} \tag{2}$$

where $\lim_{t\to\infty}\left[\frac{\rho_c^{2(t+1)}-e^{-2(t+1)\mathcal{D}}}{\rho_c^2-e^{-2\mathcal{D}}}\right]=0$ by the aforementioned framework assumptions.

I define t^{one} as the time where the variance of P_t is minimised. Solving for this time horizon yields the following indirect expression that provides important insight into the factors influencing the appropriate event window length:

$$t^{one}:\mathcal{D}\left[e^{-2(t+1)\mathcal{D}}\right]+ln(\rho_c)\rho_c^{2(t+1)}=\left[\frac{(e^{-2\mathcal{D}}-\rho_c^2)}{2}\right]\frac{\sigma_n^2}{\sigma_c^2}. \tag{3}$$

Two important findings from Equation 3 are that $\frac{\partial t^{one}}{\partial\sigma_n^2}<0$ and $\frac{\partial t^{one}}{\partial\sigma_c^2}>0$. In other words, an increased presence of unrelated news (cognitive noise) results in the time where the variance of the asset price is minimised to decrease (increase).[2] The dynamics caused by these two components give formal insight into why strictly using narrow event windows isn't appropriate.

2.2 Estimator Form

The dynamics described by Equation 3 provide insight into the trade-offs for a *single* news announcement. To apply this framework empirically such that the methodology of this paper is motivated, this concept must be extended to the *average* price reaction across many news releases. Therefore, the goal of this paper is not to find t^{one} for any single event, but to systematically estimate t^*, the time at which the market fully reacts to news announcements *on average*. Formally, consider N news announcements and the price of one asset market. For each news i that is released at time t, the asset price $P_{i,t}$ and its components will respond to the announcement. Therefore, I define t^* as the optimal time horizon that minimises the mean squared error (MSE) between $P_{i,t}$ and $P_{i,t}^f$ for all N news:

$$t^*:\min_t\frac{1}{N}\sum_{i=1}^{N}\left(P_{i,t}-P_i^f\right)^2=\min_t\frac{1}{N}\sum_{i=1}^{N}\left(\varepsilon_{i,t}^c+\varepsilon_{i,t}^n\right)^2 \tag{4}$$

[2] 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.

However, assume that the fundamental component is unobservable to the econometrician. Instead, suppose that the econometrician observes a noisy signal of the fundamental component, $s_i = P_i^f + \xi_i$, where $\xi_i \sim \mathcal{N}(0, \sigma_s^2)$. By making the core assumption that the sum of the asset price noise components, $(\varepsilon_t^c + \varepsilon_t^n)$, and the signal noise are *independent*, I am able to derive the following expression for the minimisation problem of the MSE:

$$
\begin{aligned}
t^* : \min_t \frac{1}{N} \sum_{i=1}^{N} (P_{i,t} - s_i)^2 &= \min_t \frac{1}{N} \sum_{i=1}^{N} \left(P_i^f + \varepsilon_{i,t}^c + \varepsilon_{i,t}^n - P_i^f - \xi_i \right)^2 \\
&= \min_t \frac{1}{N} \sum_{i=1}^{N} \left(\varepsilon_{i,t}^c + \varepsilon_{i,t}^n - \xi_i \right)^2 \\
&= \min_t \frac{1}{N} \sum_{i=1}^{N} \left[\left(\varepsilon_{i,t}^c + \varepsilon_{i,t}^n \right)^2 + \xi_i^2 - 2\xi_i \left(\varepsilon_{i,t}^c + \varepsilon_{i,t}^n \right) \right] \\
&= \min_t \left\{ \mathbb{E}\left[\left(\varepsilon_{i,t}^c + \varepsilon_{i,t}^n \right)^2 \right] + \mathbb{E}\left[\xi_i^2 \right] - 2\,\mathbb{E}\left[\xi_i \right] \mathbb{E}\left[\left(\varepsilon_{i,t}^c + \varepsilon_{i,t}^n \right) \right] \right\} \\
\implies t^* : \min_t \frac{1}{N} \sum_{i=1}^{N} (P_{i,t} - s_i)^2 &= \min_t \left[\frac{1}{N} \sum_{i=1}^{N} \left(\varepsilon_{i,t}^c + \varepsilon_{i,t}^n \right)^2 + \sigma_s^2 \right] \qquad (5)
\end{aligned}
$$

Because the addition of a constant does not affect the optimisation problem of the MSE with respect to time t, this derivation implies that the econometrician is still able to solve for the optimal time horizon, t^*, by observing *only* the noisy signal of the fundamental component, s_i. Note that this optimisation problem is an asymptotic result. In other words, when given infinitely many news events, the precision of the signal has zero effect on finding the optimal time horizon, t^*. However, in finite sample applications such as the empirical monetary policy literature,[3] the precision of the signal can determine the feasibility of estimating t^*. An equivalent but important interpretation of the optimal time horizon is that t^* is the time in which the average impact of the noise components on the asset price is minimised, resulting in P_i^f (and subsequently s_i) to have the largest "share" in the asset price.

[3]For example, the FOMC only release eight scheduled monetary policy announcements in a year.

2.3 Simulations

In this subsection, I simulate the asset price process over time for multiple news announcements. The simulation illustrates the effect of cognitive noise and unrelated news on the optimal time horizon for price responses and demonstrates why a good signal is required for this time horizon estimation, both motivating the necessity of my methodology.

The simulation assumes that news is released at time $t = 0$. The fundamental price component, $P^f_{i,t}$, responds by jumping to and remaining at real value $P^f_i \in [-100, 100]$. Simultaneously, the cognitive noise component jumps to a random value within $[-100, 100]$ whilst unrelated news is equal to zero at $t = 0$. The noisy signal observed by the econometrician, s_i, is assumed to have its error component distributed normally with mean zero and finite variance. To analysis this on average, I simulate the price process and the noisy signal for $N = 10,000$ news announcements up to time $t = 100$, calculating both the true and estimated MSEs using P^f_i and signal s_i, respectively. Finally, the true and estimated times at which the market fully reacts on average, t^* and $\hat{t}$, can be determined according to Equation 4.

2.4 Simulation Results

Three scenarios are considered for the asset market price responding to the release of news: one that exhibits cognitive noise but little unrelated news, one with unrelated news but little cognitive noise, and one with both cognitive noise and unrelated news. The simulation parameters corresponding to these three scenarios can be found in the topmost eight rows of Table 1.

Reading the columns of the bottom two rows of Table 1 from left to right, one can see that an asset market possessing a lot of cognitive noise with little unrelated news will have a longer optimal time horizon. The middle column shows the opposite: when faced with a lot of unrelated news but little cognitive noise, t^* becomes very small. Both these results follow the dynamics predicted by Equation 3. Intuitively, when markets need more time to fully react to news, this means the optimal time horizon should be longer. In contrast, when markets are able to react quickly to the news and there is the presence of unrelated information coming out over time, using a short event window would be more appropriate. The rightmost column displays the most "realistic" scenario for an asset market: both cognitive noise and unrelated news exist. In such an event, the optimal time horizon lies somewhere between the two extreme scenarios.

Importantly, the simulations also present minimal differences between t^* and $\hat{t}$—the true and estimated time horizons, respectively—when using only the signal s_i. Therefore, a "good" signal allows for the possibility of estimating the time horizon that reflects when markets have fully reacted to news on average. However, how does one obtain a "good" signal of the fundamental price component?

3 Input and Output Data

The sample period for my analysis runs from May 1999 through October 2019. Because the FOMC is the principal entity of the Federal Reserve System that determines monetary policy for the U.S., the Committee is closely watched by markets, which react to regularly scheduled announcements about the its policy actions and forecasts. Of particular importance are the released FOMC statements, which are the initial announcements of monetary policy. Because financial markets have been known to dissect and react to these statements word-by-word,[4] understanding when financial markets fully react to the information contained in these headline text is important for event study techniques. However, the mapping from "full" monetary policy communication to financial market asset price reactions is non-parametric and difficult to fully capture with popular text analysis methods in empirical macroeconomics. Approximating this underlying relationship—necessary for obtaining the signal needed for estimating the optimal event window length—motivates the text-analysis neural network approach in my paper. Before detailing the application of my method for sys-

[4]E.g., CNBC coverage of the January 2025 FOMC statement text.

tematically estimating optimal event window lengths, I first provide descriptive information on the FOMC statements (i.e., the inputs) and the financial market asset prices considered in this paper (i.e., the outputs). Table 2 provides an overview of the employed inputs and outputs data.

3.1 Inputs: FOMC Statements

The decisions of the FOMC are typically announced in a press release shortly after its meeting concludes. Scheduled meetings occur eight times per years an are typically 6–8 weeks apart. Occasionally the FOMC will hold unscheduled meetings whenever they deem policy action is needed before the next scheduled meeting occurs. I drop the statements of these unscheduled meetings from my sample because I want to ensure the change in asset prices within event window lengths around the publication time is driven by the content of the statements themselves and not confounded with the surprise that there was an FOMC meeting. I source the scheduled statements from the Board of Governors of the Federal Reserve System website.[5] This selection process results in the current version of this paper to have a sample size of 165 statements.

Text Pre-processing: To prepare my sample of FOMC statements for the neural network approach, I pre-process all FOMC statements by converting them into plain text format, changing the text coding into standardised UTF-8 format (e.g., change length of "-"), and ensuring the spacing between words is one space. In addition, I remove all URLs, the FOMC member voting record found at the end of each statement, the list of regional bank request approvals, and mentions of release timestamps. Although papers such as C Madeira and J Madeira (2019) have shown that voting records affect stock market reactions, no effect was found for interest-based assets such as Treasuries. I prioritise removing the voting records such that the main economic discussions within the FOMC statements are entirely considered by the neural network with its hard constraint on the number of words when approximating

[5] https://www.federalreserve.gov/monetarypolicy/fomc.htm

the underlying relationship. More information about this limitation is discussed in Subsection 4.[6]

Content and Evolution of Statements: A typical FOMC statement begins with a general discussion of current macroeconomic conditions and then communicates the Committee's expectations for the future of the macroeconomy. The statement then mentions the Committee's goal of achieving maximum employment and price stability concludes with the new Federal Funds and discount rates. Following the Great Recession of 2008–2009, these statements included discussion about unconventional monetary policy, such as quantitative easing programmes. Because this period of time saw an increase in complexity in the language of FOMC communication and the inability of the Committee to use rate changes to influence market expectations about monetary policy, the statements grew rapidly in length up to 2014, as seen in Figure 3. This trend gradually reverses after 2014, but the statements are still longer on average than those before the Great Financial Crisis.

The following example is an excerpt of the FOMC statement released on 01 August, 2018:

> Information received since the Federal Open Market Committee met in June indicates that the labor market has continued to strengthen and that economic activity has been rising at a strong rate. [...]
>
> The Committee expects that further gradual increases in the target range for the federal funds rate will be consistent with sustained expansion of economic activity, strong labor market conditions, and inflation near the Committee's symmetric 2 percent objective over the medium term. Risks to the economic outlook appear roughly balanced.
>
> In view of realized and expected labor market conditions and inflation, the Committee decided to maintain the target range for the federal funds rate at 1-3/4 to 2 percent. The stance of monetary policy remains accommodative, thereby supporting strong labor market conditions and a sustained return to 2 percent inflation.

[6] Another reason why I choose to remove the voting record excerpt from the statement text is because the vast majority of my approach outputs are interest-rate futures price changes, meaning the removal should not have much impact on the systematic estimation of the optimal event window length for these markets. Nonetheless, futures versions of this paper will have the approach inputs contain the voting records.

3.2 Outputs: Interest-rate and Equity Futures

The output data for the neural network approach of approximating the underlying relationship are interest-rate and equity futures prices for various financial markets. All asset prices come from the Thomson Reuters Tick History database and are obtained from Refinitiv. I use these asset prices at the intraday frequency for all analyses because it allows for the consideration of event window lengths frequently seen in the high-frequency identification literature, such as the most popular choice of 30 minutes. More specifically, the change in expected interest rate paths can be measured via the variation in prices of interest rate futures in event windows surrounding FOMC announcements.

Federal funds futures and Eurodollar futures contracts are considered because many high-frequency monetary policy surprises are constructed based on the change in expected interest rates at the time horizons measured in these asset types (Kuttner, 2001; Gürkaynak, Sack, and Swanson, 2005; Gertler and Karadi, 2015; Nakamura and Steinsson, 2018; Jarociński and Karadi, 2020; Handlan, 2022b; and others). The market for federal funds futures is liquid enough to measure expectations of monetary policy roughly three months out, specifically capturing expectations about the federal funds rate after the current and next FOMC meetings (i.e., $FF1, FF2, FF3, FF4$). Eurodollar futures can be used as instruments to measure expectations beyond three months. As an example in Acosta et al. (2024), a market participant trading on date t of quarter q based on their expectations on interest rates two quarters from now would trade the second-outstanding or 2-quarter Eurodollar future, with the settlement towards the end of quarter $q+1$. This paper considers Eurodollar futures capturing market expectations from about four months to one year ahead (i.e., $EDcm2, EDcm3, EDcm4$). For longer time horizons, systematic estimation of optimal event window lengths is performed on financial markets for Treasury futures with horizons two ($TUc1, TUc2$), five ($FVc1, FVc2$), ten ($TYc1, TYc2$), and thirty years ($USc1, USc2$), whose time horizons were approximated by Gürkaynak, Kisacikoğlu, et al. (2020) to be two, four, seven, and fifteen years ahead, respectively. I also focus on equity markets, particularly the S&P 500 Index and its E-mini futures (i.e., $SPX, ESc1, ESc2$), for two reasons. First, aside from interest rates, equities are one of the most studied asset class in the empirical monetary policy literature. Second, stock index futures are traded outside of regular trading hours, providing sufficient data quality for me to consider a wide variety of event window lengths.

Dependent Variable Construction: Price levels for these futures contracts are collected at 10-minute intervals, starting from 10 minutes before an FOMC statement release through 18 hours after publication. The output of interest for the neural network approach is the log-price differences of each futures contract constructed within event window lengths starting 10 minutes before and $t + n$ minutes after the FOMC announcement,

$$DP_{t+n} = ln\left(\frac{P_{t+n}}{P_{t-10}}\right), \tag{6}$$

I have the neural network approach of the systematic estimation only consider price log-differences within event window up to 70 minutes in length.[7]

4 Systematically Estimating Optimal Event Windows

At the core of systematically estimating optimal event window lengths is the underlying, nonparametric relationship between the monetary policy communication and the financial market price reactions. Obtaining the text-based signal needed for the estimation is only possible if this mapping can be approximated with precision. A general requirement for this precision is that the approximation method is able to consider and quantify the full information content contained within the FOMC statement text. Otherwise, the method would fail to account for all of the possible dimensions of monetary policy communication from the statement driving financial market reactions.

[7]Price log-differences calculated within longer event windows are not considered due to computational and financial constraints, but are still outputs of interest for future versions of this paper.

When considering the text analysis methods that are popular in the monetary policy literature, most can be described as "fitting predictive models on simple counts of text features" (Gentzkow et al., 2019). However, these methods often miss how words within and across sentences relate to each other. For example, the phrases "*employment* went up, but *inflation* did not" and "*inflation* went up, but *employment* did not" would produce the same measures. Alternatively, methods that measure the frequency of neighbouring words, called "n-grams", often miss information spread out across a sentence. For the following phrase, "economic growth slowed, but is expected to pick up pace later this year", a trigram would count "economic growth slowed", but would miss the point of the sentence that economic growth will reverse direction and expand later in the year. In other words, these popular methods cannot realistically capture the "full" information content of text.[8]

In contrast, text-analysis neural networks can approximate the complex relationships between words such as context and interdependencies. Using these methods, the words "slowed" and "pick up pace" could both be associated with "economic growth" for prediction, even though these words are not all adjacent within the sentence. Indeed, with other social sciences observing success in applying natural language processing, economics could witness similar benefits when using these methods to study the monetary policy communication (Gentzkow et al., 2019).

4.1 Approach: XLNet-Base, a Neural Network for Text Analysis

The approximation approach employed behind the systematic estimation is the XLNet-Base language model from Yang et al. (2019), which builds upon the transformer architecture introduced by the seminal paper of Vaswani et al. (2017).[9] The neural network abandons

[8]If it was possible to account for every possible combination of words and phrases of interest, then these frequency measures would be able to quantify the "full" information content of text like FOMC statements.

[9]The text-analysis neural network is open-source, pre-trained, and has 12 hidden layers (each with 768 dimensions), 12 self-attention heads (each with 64 dimensions), a vocabulary size of 32,000 word tokens, and two feed-forward layers with 768 and 3072 dimensions, respectively, ultimately resulting in approximately 117 million parameters. More information about the neural network can be found on the open-source platform https://huggingface.co/xlnet/xlnet-base-cased.

the literature technique of "corrupting" input text through masking the words of prediction-interest and assuming that these masked words are independent of each other. The former practice can lead to discrepancies when subsequently training the network on a different set of text without masking. The latter assumption is often violated.[10] Instead, XLNet-Base considers all possible information from all permutations of words around the words of interest in its pre-training phase. As a result, the neural network can learn context and dependencies bi-directionally without the usage and weaknesses of masking. Furthermore, XLNet-Base is better suited for tasks prioritising context and semantics compared to recently popular generative pretrained transformer models (e.g., ChatGPT), which can only process and learn text in a unidirectional manner.[11] The permutation language modelling objective allows for XLNet-Base to be highly versatile and suitable for being fine-tuned for tasks beyond simple word prediction. Relevant to this paper is the regression task of approximating the underlying relationship between FOMC statement text and financial market price reactions. I start with the off-the-shelf architecture, parameters, weights, and general English language skills of the XLNet-Base. I then fine-tune the neural network to "transfer" its knowledge into the task of approximating the underlying relationship and obtaining the text-based signal.[12]

4.2 The Inputs, Outputs, Approach, and Optimal Window Length

Recall from the conceptual framework in Section 2 that within any given event window, the asset price changes will be mixtures of the fundamental price components and noise factors. It is *only* within the optimal event window length that on average, the impact from the noise factors will be minimised, simultaneously resulting in both the fundamental price components and its noisy signals to have the largest "shares" of the price changes.

[10] Consider the example phrase, "The Federal Open Market Committee decided to increase its target rate". The words "target" and "rate" are masked. However, these words still share implicit relations to each other.

[11] All large language models are defined by predicting a word using only those that came before it. This "left-to-right" operation is why such models are commonly labelled as "generative" models.

[12] This application is only possible thanks to Yang et al. (2019) and others in the machine learning literature demonstrating that the transfer learning approach reduces training data requirements whilst achieves similar accuracy in new tasks.

Relative to the inputs, outputs, and approximation approach detailed earlier in this section, the signal can be interpreted as the *change in futures prices, within a given event window length, that is prediction by the neural network's approximation of the underlying relationship between the FOMC statement text and the observed futures market price variation*. In other words, because the observed price changes within any sub-optimal event window will have the average impact of cognitive noise and unrelated news not minimised, this causes the approximation of the underlying relationship by XLNet-Base to struggle making predictions about the price change attributed to only the FOMC statement text. In contrast, only within the optimal event window length will the average impact of noise be minimised on the price changes, allowing the neural network's approximation to have relatively the best performance in predicting the text-based signal. This simultaneous relationship between the optimal window length and text-based signal is what drives my systematic estimation method, which I provide an overview below:

1. For a given event window length, I have XLNet-Base regress the price changes of a futures contract on only the text content of FOMC statements and assess its predictive performance and signal precision.

2. I have the neural network perform this regression for event windows increasing into length up to 70 minutes.

3. The event window length that resulted in the text-analysis neural network to have the best approximation of the underlying relationship through its predictive performance is what I define as the optimal event window length for that futures contract.

With this summary of the systematic estimation method in mind, I move to explain the details behind preparing the inputs and outputs data specifically for the approximation by the neural network.

4.3 Stratified-sampling Cross Validation

I begin the systematic estimation by splitting my sample into training and testing subsamples five times, where 20 per cent of FOMC statements belong in each testing subsample. Splitting the statement observations is specifically conditioned by the type of decision the FOMC made to the target federal funds rate, who the FOMC Chair was, if the date was pre- or post-2007, and by imposing both subsamples to have equal distribution of statements according to word count. This process yields five distinct training-testing subsample splits such that no testing subsample shares FOMC statements with one another.[13]

These splits can be thought of as consisting of input-output pairs, where the inputs are the FOMC statements and the outputs are the calculated futures price log-differences. For each 10-minute interval and each futures contract maturity, I train XLNet by refitting its parameters to approximate the relationship between the text of FOMC statements and the price log-differences on the training subsample and then tested on the held-out subsample. This process is repeated five times, once for each split. The final accuracy for each event window length is the average performance across all five test splits. This methodology ensures a robust measure of out-of-sample performance and accounts for any variation in the network's predictions coming from the splits themselves.[14]

For each split, I restrict the context window of XLNet (i.e., the number of word tokens the neural network considers as a single input and retains in its memory) to be a sequence length of 512 word tokens for each FOMC statement.[15] Because the average number of words found in FOMC statements is roughly 327 (with a peak of 800 words), I assume that XLNet should still have adequate headroom to understand the full meaning of most statements. Relatedly, a list of the neural network main hyperparameters for the fine-tuning process can

[13]This process is called "stratified sampling 5-fold cross validation in the machine learning literature.

[14]Stratified sampling 5-fold cross validation minimises the differences between the population distribution of FOMC announcement characteristics and the subsample distributions of these characteristics, which is necessary for training neural networks on finite samples through transfer learning.

[15]Tokens are the converted input text fed into the neural network. The practice is done to reduce the input vocabulary size. For example, {"decreasing", "increasing"} can be broken into the following tokens: {"de", "in", "creas", "ing"}.

be found in Table 3.

4.4 Accuracy Metrics

For each split, the primary metric considered by the neural network to judge its accuracy during fine-tuning is a *generalised* R^2 statistic defined in Hawinkel et al. (2024), which I denote as R^2_{OOS} for the rest of the paper. This statistic was chosen primarily because of two reasons. First, recall that the conventional definition of R^2 is the proportion of variance in the data that is explained by a given model. This definition breaks down when applied to non-linear methods like neural networks because the variance of the observations is no longer comprised of only the model and residual variances. In other words, squaring the Pearson correlation coefficient does not equal R^2. Second, the formula for R^2_{OOS} is adjusted to more appropriately assess out-of-sample—not in-sample—model performance. Mathematical details of the generalised R^2 statistic can be found in Appendix A.

The interpretation of R^2_{OOS} can be better understood through a brief discussion about the underlying relationship that the neural network is approximating and using to predict, which is the nonparametric function mapping the text of FOMC statements to asset price changes. As is standard in the machine learning literature, the predictive quality of models is compared to the common baseline that states there is *no* relationship between the FOMC statement text and asset price changes and naively predicts with the in-sample average. When using the neural network to instead approximate this relationship and predict asset price changes for statements in the testing subsample, the R^2_{OOS} therefore states how much predictive error from naively using the in-sample average has been reduced.

Other related metrics that are tracked by XLNet during its fine-tuning process are the out-of-sample Pearson correlation coefficient ρ between the predicted and actual observations, the out-of-sample mean absolute error, and the in-sample mean squared error. The last criterion is important for determining if the network is learning the relationship between the FOMC statement text and the price log-differences or not.

The decisive criterion for systematic estimation is the out-of-sample R^2 *averaged across sample splits* for each 10-minute interval of each futures contract maturity:

$$\overline{R^2_{OOS}} = \frac{\sum_{i=1}^{K} R^2_{OOS}}{K}, \tag{7}$$

where $K = 5$ is the number of sample splits. The statistic measures the average improvement in performance of the neural network approximating the relationship between FOMC statements and the price reactions of markets within a given event window length, relative to naively predicting with the in-sample average. In other words, the optimal window is the length that yields the largest average improvement in generalisability by the neural network, a property that is only possible when the observed asset price changes are minimally impacted by cognitive noise and unrelated news.

4.5 Fine-tuning the Neural Network for Approximation

The machine learning literature evaluates neural networks primarily under the criterion of prediction and places no meaning on the network's parameter estimates because network parameters do not have the same interpretation as those of parametric models (Athey and Imbens, 2019). Therefore, my paper cannot describe the causal effect of one word over another within FOMC communication on market expectations. Instead, the training process behind the neural network allows me to approximate this relationship and use its predictions to attribute what event window size best reflects the markets' full reaction to the FOMC statements.

When fine-tuning the network, overfitting becomes an inevitable issue due to XLNet having 110 million parameters. On a per-split basis, this issue contributes to the difference between R^2_{OOS} and the equivalent calculated for the training sample. I minimise this contribution by limiting XLNet's training through the number of training iterations used and the learning rate. Deploying too many training iterations causes the neural network and its weights to perfectly match the training data whilst deteriorating its out-of-sample prediction accuracy. In other words, too many training iterations causes XLNet to become less generalisable. In contrast, allowing the neural network with too few training iterations can prevent the neural network from fully learning the relationship between the in-sample FOMC statements and price log-differences. The learning rate is essentially the rate at which a neural network updates its parameters to the training data. Too high of a learning rate will result in the network forgetting information from prior training iterations during its current iteration (i.e., the weights of the network are updated too dramatically). This issue results in the network's out-of-sample predictions either degrading rapidly over fewer training iterations or remaining constant because the associated predictions stop updating. Conversely, too low of a learning rate results in XLNet to never fully learning the mapping between FOMC communication and asset price log-differences. Because I am applying the transfer learning approach, the initial values of XLNet's parameters are already optimised to understanding the general English language. Therefore, I can ensure the weighting of XLNet's parameters remain generalisable to new data by limiting how much the parameters can update both within and across training iterations.

Ultimately, the process of training a neural network is a balancing act: I train XLNet to meaningfully approximate the mapping from FOMC statements to asset price log-differences, but do so without overfitting to the point that the predictions are non-generalisable. I perform this balancing act by following a two-step process with the limitations on the aforementioned hyperparameters in mind. First, I set the maximum number of considered training iterations to be 2040 steps (120 epochs). I then perform what the literature calls a "hyperparameter sweep" on the learning rate. Specifically, Bayesian optimisation is performed on the set of learning rates XLNet uses when fine-tuning up to 2040 training steps.[16] During the sweep, the accuracy metrics mentioned in Subsection 4.4 are tracked in the training process for each considered learning rate. Training XLNet is stopped at the iteration where

[16]The set of considered learning rates are $[1e-5, 9e-5]$ and Bayesian optimisation assumes a uniform distribution.

in-sample accuracy increases, but out-of-sample accuracy decreases. At the end of the sweep duration of 24-48 hours for each split, the learning rate and training iteration that yields the highest R^2_{OOS} is selected. Because out-of-sample predictions can be volatile during applications of transfer learning on finite sample sizes, I select the version of XLNet from the training iteration that exhibits this simultaneity only if future iterations output a permanently worse out-of-sample prediction accuracy. The platform behind the aforementioned fine-tuning process is Simple Transformers from Rajapakse et al. (2024), which simplifies the process of training, experimenting, and performing inference with Transformer model architectures for natural language processing tasks (e.g., Simple Transformers automatically selects the appropriate tokenizer when selecting XLNet).

4.6 Addressing Look-ahead Bias

A valid concern when using off-the-shelf neural networks for text analysis is look-ahead bias. As explained in Sarkar and Vafa (2024), look-ahead bias occurs whenever these networks predict values in the past using information in the future. This issue stems from how most text-analysis neural networks are initially trained with a large amount of data from many sources, which increases the probability that information from the future was used in this initial training of the network weights.[17] I argue that the effects of look-ahead bias on the neural network method used for systematic estimation of appropriate event window lengths are mitigated for two reasons. The first reason is from the initial training corpora of XLNet itself and the second pertains to the language composition of the FOMC statements.

First, However, XLNet-Base addresses the concern of look-ahead bias because its initial training data was restricted by its authors to *only* BookCorpus and the entire English Wikipedia. This restriction makes it highly unlikely for the neural network to learn any information about the intersection of FOMC communication and futures markets price re-

[17]The issue of look-ahead bias is especially prevalent for modern large language models (e.g., ChatGPT) because their architectures are not open-source and their pre-training data sources are neither fully known nor publicly accessible.

actions during its pre-training phase. I also note that Yang et al. (2019) showed that this restricted initial training data does not negatively impact the generalisability of the neural network when compared to other models.

Look-ahead bias is also mitigated in my application of XLNet-Base because of the temporal anonymisation of the information content in the FOMC statements. Similar to Glasserman and Lin (2023), the language composition of the pre-processed statements has no references to relative times t and $t+1$. As a result, even if XLNet-Base was trained with FOMC statements that were in the future relative to the statement it is being asked to predict the price log-difference, the neural network does not have any necessary information to chronologically order the FOMC statements and subsequently "figure out" that its weights have been trained on future data.

5 How Long Do Markets Need to Fully React to FOMC Statements?

In short, systematic estimation of the optimal event window length can be summarised as the following exercise: the neural network is searching for the event window length where the average impact of cognitive noise and unrelated news on the variation of asset prices is minimised, allowing the neural network to approximate the underlying relationship between FOMC statement text and the asset price changes such that its out-of-sample predictions are the most generalisable on average.

Figures 4–10 present the results of this exercise for all maturities of federal funds, Eurodollar, 2-, 5-, and 10-year Treasury futures. The horizontal axis of each figure depicts the end time of the considered event windows (e.g., $t+20$ represents a 30-minute event window starting at 10 minutes before and 20 minutes after FOMC statement publication) and the vertical axis represents the variation of price changes predicted by the neural network to be solely associated with the text of FOMC statements in the testing subsample. The cross points represent $\overline{R^2_{OOS}}$ for each event window size, where the solid yellow point represents the event window length with the largest averaged out-of-sample R^2_{OOS}. For each event window size, box-and-whisker plots are shown surrounding the corresponding averages in order to better present the distribution of predictions from the neural network across sample splits.[18]

The cross points show that regardless of futures maturity and asset type, the event window that corresponds with the largest $\overline{R^2_{OOS}}$ is always at least 40 minutes in length, beginning 10 minutes before and ending 30 minutes after FOMC statement publication. In contrast, a 30-minute event window never has such association. This implication is also robust to the act of averaging the out-of-sample R^2_{OOS} of each split, as similar conclusions are reached when examining other presented metrics of the box-and-whisker plots, such as either the 25^{th} and 75^{th} percentiles: regardless of asset type and maturity, financial markets fully react to the information content of FOMC statements within a 40-minute event window *at minimum*, implying that the popular choice of 30-minute event windows is not enough time.[19]

An interesting observation is that the event window length where XLNet achieves the highest $\overline{R^2_{OOS}}$ increases with the time horizon of the considered futures. Specifically, the average systematically estimated event window for the front-month and one-month-ahead Federal Funds futures—assets used to measure market expectations about future monetary policy from the upcoming FOMC meeting—is 40 minutes in length, whereas the average window length for the two- and three-month-ahead Federal Fund futures is 45 minutes. For Eurodollar futures, which are used to measure expectations about the path of interest rates between two and four quarters into the future, the neural networks predicts markets fundamentally react to the information content of FOMC statements within a 50-minute event window. 50 minutes is also the systematically estimated window length for both 2- and 5-year Treasury futures (when averaging across the first- and second-month contract maturities),

[18]Typical standard errors and confidence bands are not calculated because there are too few data points, i.e., the number of sample splits is $k = 5$. Whilst this could be changed such that the neural network performs systematic estimation using leave-one-out cross validation, the computation and financial costs are too great to make this alternative feasible for the current version of this paper.

[19]Although not shown to avoid visual clutter, a similar conclusion is made when using the median R^2_{OOS}. The optimal event window is still never 30 minutes in length.

but the trend increases for 10-year Treasury futures, which has a systematically estimated length of 60 minutes. The optimal event window length estimated by the neural network for the S&P 500 Index shortens down to 50 minutes. One possible explanation behind this increasing trend overall is that market participants are trading futures with expectations about interest rates further into the future. These longer-horizon assets could be more influenced by belief and information uncertainty when it comes to mapping from the information content of the released FOMC statement, which are ultimately reflected in significant and larger risk premia (Piazzesi and Swanson, 2008). Additionally, Okada (2025) document that longer-duration Treasury bonds are more effected by the FOMC announcement premium in contrast to short-horizon assets due to interest rate risk. With regards to equities, it also could be possible that the systematically estimated event window is longer than the conventional 30-minutes because the asset is less directly impacted by monetary policy statements.

Relatedly, the systematic estimation of optimal event window lengths by the neural network shows that $\overline{R^2_{OOS}}$ exhibits a "hump" shape by first increasing with event window length. This trend peaks at 30–50 minutes after statement publication, where the measure begins to decline. As previously discussed in the paper, the conceptual framework factors of cognitive noise and unrelated news could be at play here. As time increases, the effects of cognitive noise decline as markets start to fully react to the monetary policy announcements. Eventually, the effects of unrelated news dominate the price reaction of futures markets, causing $\overline{R^2_{OOS}}$ of the neural network to shrink. The optimal event window length is the length where the impact from both of these components are minimised, resulting in the neural network's approximation of the underlying relationship to be the most generalisable on average, relative to using the in-sample average for prediction.

It is important to notice that for all considered event window lengths of all interest-rate and equity futures, the predictive quality of neural network achieves a positive $\overline{R^2_{OOS}}$, indicating that there is indeed an underlying relationship between the FOMC statement text and asset price changes. Table 4 summarises these results for each considered futures contract and equities. Relative to naively predicting with the in-sample average, the generalisability of the neural network increases by an additional 2–17 p.p. (7.4 p.p. on average) within the optimal event window compared to that in conventional 30-minute windows.

5.1 Different Event Windows, Different Market Responses

With the optimal event window length systematically estimated for every asset type and futures maturity, I compare the market price responses measured within these windows to those calculated within the conventional 30-minute window of the literature. Figures 11–17 depicts this exercise for all considered assets. The horizontal (vertical) axis of each sub-figure represents the price log-difference within the systematically estimated (30-minute) event window. The blue dots are the market reactions on scheduled FOMC meetings in my sample. The 45-degree line is depicted as grey.

For a simple ex post characterisation of whether markets for certain asset types and maturities under- or over-react to FOMC statements on release, I regress the price log-differences within the optimal event window lengths on those calculated within a 30-minute window through OLS. If the slope coefficient is less than one and its difference with one is statistically significant for at most $\alpha = 0.05$, then I state that the market for the futures contract and time horizons under-reacts to the information content of FOMC statements on release. Otherwise, the price reactions of the market between these two event windows are not different in general. I visually display this in the sub-figures by colouring the regression lines as red for the former scenario and as grey for the latter.

Financial markets for all futures with interest-rate-based underlying assets appear to under-react to the information content of FOMC statements on release, ex post. Furthermore, the slope of the regressions decreases as the time horizon of these assets increases. The movement of these markets could potentially be related to the post-FOMC announcement drift documented in Brooks et al. (2023) and Neuhierl and Weber (2024), where the latter specifically finds that the slow adjustment of mutual fund investors their interest rate expectations play a role in the price dynamics after the policy announcements. A notable example of this characterisation can be seen in the 16 December, 2008 FOMC meeting, where the federal funds rate range was cut down to between 0% and 0.25% in response to the Great Recession. In addition to being the first time that the federal funds rate would be below 1%, the decision was also a surprise to financial markets, who were expecting a reduction to only between 0.25% and 0.5%. When combined with how the FOMC statement itself stated that the committee would "employ all available tools to promote the resumption of sustainable economic growth and to preserve price stability", these characteristics possibly contributed to the markets needing more time than typically assumed to fully react to the information describing the weakening U.S. macroeconomy. The top sub-figure of Figure 18 presents the market price reactions for all considered Eurodollar futures maturities on this FOMC meeting date. One can immediately see that as the event window length expands, the change in price becomes increasingly positive compared to the initial reaction within a 20-minute window.

Financial markets for the S&P 500 Index were also found to systematically under-react to the FOMC statement releases, ex-post, corroborating findings from Neuhierl and Weber (2024) on stock return movements in the Center for Research in Security Prices value-adjusted index and from Golez et al. (2025) about belief under-reaction of individual equities, possibly due to individual equity market participants having difficulty fully reacting to the signal content in FOMC announcements. However, it should be noted that the S&P 500 Index was also the market that saw the most price reversals, particularly from negative to positive log-differences as as time progressed after the release of some FOMC statements. One good example can be seen in the S&P 500 Index market response to the 16 September, 2008 FOMC statement, which is depicted in bottom sub-figure of Figure 18. Within 20 minutes after statement release, equity markets responded negatively to the release. Interestingly, the price log-difference reversed signs and continued to grow until market close. A possible explanation behind the reversal could be that the beliefs of equity markets themselves reversed when reading the FOMC's decision to maintain interest rates. In other words, the equity market could only fully react to the relatively positive information behind the FOMC's decision with more time, allowing cognitive noise to die out and the associated negative "knee-jerk" price reactions to reverse. Indeed, Bordalo et al. (2024) documents that over-reactions are a common occurrence in stock markets and will reverse as market beliefs "correct" themselves with time.

Overall, these figures from the systematic estimation and ex post characterisation support the idea that the optimal event window length is not a parameter whose value we should simply assume. Instead, I document how the event window lengths that best reflect market full reactions to FOMC statements varies across asset types and time horizons systematically.

6 What Happens to Monetary Surprises and Shocks?

The systematic estimation of this paper has shown that the optimal event window length is always longer than the standard assumption of 30 minutes regardless of asset type and time horizon. However, how are monetary policy surprises and shocks affected when changing to the optimal window lengths?

Proper investigation into this question requires that I use a common event window length when constructing the surprises because the "invertibility", or "spanning" (Duffee, 2013), of information about macroeconomic variables from the yield curve is well-defined for a temporal cross-section of yields. In contrast, it is not currently known if these macro-finance term structure models are well-defined for different points of time on the yield curve. As a result, I construct monetary policy surprises for each of the window lengths found to be optimal by the neural network: *40-, 50-, and 60-minute windows.* The rest of this section uses the same intraday price data on interest rate futures and considered FOMC meeting dates as described in Section 3.

6.1 Differences in Monetary Policy Surprises

For each FOMC meeting date, I construct interest rate surprises within 30 minutes and the three found optimal event window lengths. Following Kuttner (2001), Gürkaynak, Sack, and Swanson (2005), Nakamura and Steinsson (2018), and others, I use federal funds rate to cover interest rate expectations up to three months out, Eurodollar futures to capture expectations from about four months to one year ahead, and Treasury futures for interest rate expectations out to fifteen years. Appendix B provides details behind the conversion from changes in futures contract prices to interest rate surprises.

Figure 19 plots the correlation between the monetary policy surprises calculated within the optimal event window lengths v. 30 minutes. The horizontal axis depicts the time horizon of the surprises (e.g., "0–1M" represents the interest-rate surprise for the FOMC meeting happening in the current or next month). The red-dotted, yellow-dashed, and green-mixed lines represent the correlations calculated for surprises measured within the optimally-found 40, 50, and 60 minutes, respectively. The blue-solid line represents the correlations averaged across the three optimal window lengths. For all time horizons of all surprises, we see that the correlations decline when increasing the optimal event window length. Increasing the time horizon of the surprises also sees the correlation fall by a larger magnitude under longer optimal window lengths. For example, whilst monetary policy expectations about current and next FOMC meetings are more or less identical regardless of optimal window choice, the differences between 30- and 50-minute windows result in a 10% decline in the coefficient when looking at monetary policy surprises out to fifteen years ahead. In other words, as expectations about monetary policy are further into the future, calculating interest rate surprises become more sensitive to the choice of event window lengths imposed around FOMC statement releases.

6.2 Differences in Monetary Policy Shocks

In this subsection, I use the interest rate surprises calculated within 30 minutes and the optimal event window length as financial instruments to identify exogenous variation in monetary policy through several popular methods in the literature. I choose to include interest rate surprises from Treasury futures in my instrument set to help prevent the understatement of monetary policy stimulus during the effective lower bound period (Brennan et al., 2024; An et al. (2025)).[20] For conciseness, I choose to use the *median* of the window lengths found to be optimal by the neural network: *10 minutes before and 40 minutes after statement release.*[21]

Shock Construction: I construct monetary policy shocks following the methods of Gürkaynak, Sack, and Swanson (2005), Nakamura and Steinsson (2018), and Jarociński and Karadi (2020) (henceforth GSS, NS, and JK, respectively). Rather than keep track of the entire expectations path of interest rates implied by futures prices, the authors of these papers reduce this dimensionality using principal component analysis on multiple monetary policy surprises to extract the common variation in one or two dimensions.[22,23] GSS use the first and second principal components to identify two shocks (factors) due to the multi-dimensional nature of monetary policy. The authors rotate both components such that the second component has no effect on interest-rate surprises for the current federal funds rate, yielding the "target" and "path" factors of monetary policy. NS and JK use only the first principal component because, as explained in Bauer and Swanson (2023), the first principal component is essentially a weighted average of the target and path factors. To account for possible

[20] For my sample period, the effective lower bound of the federal funds rate is defined as defined as 16 December, 2008 through 16 December, 2015.

[21] I also perform the same exercise for the optimal 40- and 60-minute windows as a robustness check in Appendix C.

[22] Principal component analysis uses eigenvalue decomposition of a given dataset's covariance matrix to project the data onto new dimensions based on its variance. The first principal component, representing the first coordinates on the new dimensions, captures the largest common variation of the original variables. The second principal components captures the second largest common variation and so on.

[23] The main results of JK use the implied interest-rate surprises from $FF4$. However, the first principal component of multiple surprises are used in the modern update of the paper's shock: https://github.com/marekjarocinski/jkshocks_update_fed

information effects from the central bank, JK impose sign restrictions on the first principal component based on its co-movement with stock market changes.[24] I make the units for all shock series the same by re-scaling each of them to be one-for-one with the daily change in the zero-coupon, nominal one-year Treasury yield. I summarise the names, notation, and construction of each of the considered monetary policy shock series I will be working with to investigate the effects of event window length choice in Table 5. Additionally, Table 6 provides summary statistics of each of the shock series. Because these methods together account for the various characteristics of monetary policy, such as its impact beyond the immediate horizon, its multi-dimensional impact, and the possible existence of information effects, any differences found in the shocks and their effects from this exercise would be the impact of event window choice.

Visual Shock Differences: To begin my investigation, I plot the shock series constructed in both event window lengths, displayed in Figure 20. For each sub-figure, the horizontal axis depicts the FOMC statement release dates. The vertical axis are percentage points after re-scaling each shock to be one-for-one with the daily change in the nominal one-year Treasury yield. The black-solid and red-dotted lines represent the shock series derived from 30-minute and optimal window lengths, respectively. Regardless of construction method, we see that much of the peaks and troughs of shocks derived within 30 minutes see larger values in magnitude at many of those FOMC statement release dates for shocks constructed using optimal window lengths.[25] For example, both the December 2008 and March 2009 FOMC meetings see larger negative shocks by 0.03–0.06 p.p. (3–6 basis points) in magnitude when using the optimal event window length, possibly suggesting that the full impacts of the information content within the FOMC statements aren't yet captured within 30 minutes.

Another episode worth pointing out is the August 2011 FOMC meeting date, where the

[24] I calculate stock market changes within the same event window length used to measure the monetary surprises.

[25] Plots for GSS_T are not shown because regardless of window choice, the shocks are essentially identical. This similarity makes sense since markets of all time horizons need little time to fully react to the immediate federal funds rate change in the FOMC statements.

statement maintained the federal funds rate range between zero and 0.25%, but was the first communication that included explicit dates on the expected path of monetary policy in its forward guidance language (Crump et al., 2013). We can see that the optimal event window length is associated with a more negative monetary policy shock in either GSS_P or NS_{MP} on this release date. When imposing the sign restrictions of Jarociński and Karadi (2020) however, the negative central bank information shock is the only component that is more negative by roughly 33%. One possible interpretation of these differences is that because the federal funds rate was already at the zero lower bound, language indicating that the future path of the federal funds rate would remain at these low levels could be interpreted as an information surprise about weaker economic conditions than initially anticipated. The full extent of this negative information shock might only materialise when financial markets are given enough time to react to the statement.

On the other hand, changing event window lengths can result in "shifts in importance" in the composition of the monetary policy shock. When comparing JK_{MP} and JK_{CBI} derived with a 30-minute window on the September 2008 FOMC meeting, the monetary policy shock is the main effect from the statement release, whilst central bank communication is close to zero. When using a 50-minute window however, this composition reverses. Looking at the statement from this FOMC meeting, we can see that the forward guidance language from the central bank suggested moderate expected growth due to accommodative monetary policy and its efforts to promote liquidity in financial markets. Combined with its decision to hold the federal funds rate range steady, market participants would likely update upwards their views about economic prospects. In line with a positive central bank information shock, the S&P 500 increased in value during trading hours.

When comparing the identified shocks from JK overall, JK_{CBI} sees a higher frequency of increased amplitude when increasing the event window length. In contrast, JK_{MP} sees smaller amounts of differences due to event window choice, aside from several instances of larger peaks and troughs in the shock. One likely explanation for the larger differences in the central bank information shock is a combination of the changes to the S&P 500 Price Index and the imposed sign restrictions of the construction method.

Responses of Interest Rates: I now look at how the event window choice affects the impact of monetary policy shocks from scheduled FOMC statement release dates on nominal and real interest rates for different maturities. I use the daily change in Treasury yields from Gürkaynak, Sack, and Swanson (2005) and daily change in treasury-inflation-protected-security (TIPS) yields from Gürkaynak, Sack, and Wright (2010) to represent nominal and real interest rates, respectively.[26] For both sets of dependent variables, I calculate the daily changes using the end-of-day yields for the day of and before the FOMC announcement. Note that both the 30-minute and optimal event window lengths used to construct the monetary policy shocks are nested within the daily window for Treasury and TIPS yield changes. This timing restriction prevents the yield changes to affect the shocks. The regression specification is as follows:

$$y^{i,j} = \beta_0^{i,j,k,l} + \beta_1^{i,j,k,l}(Shock)^{k,l} + \varepsilon^{i,j,k,l} \tag{8}$$

where i indicates daily changes in Treasury or TIPS yields as the regressand, j indexes the horizon of the yield, k denotes the considered monetary policy shock used as the regressor, and l denotes whether the shock was constructed within the optimal event window length or 30 minutes.

Regression results for the responses of nominal and real interest rates to the monetary policy shocks within different event windows are presented in Table 7 and Table 8, respectively. In both tables, each estimate comes from a separate OLS regression of the form described in Equation 13. Starting from the left, columns 3–5 (2–4) of Table 7 (Table 8) contain estimates coming from regressions where the dependent variable is the daily change in nominal (real) yields and the independent variable is a monetary policy shock series constructed within 30 minutes around scheduled FOMC announcements. Estimates in columns

[26] Treasuries: https://www.federalreserve.gov/data/nominal-yield-curve.htm, and TIPS: https://www.federalreserve.gov/data/tips-yield-curve-and-inflation-compensation.htm

6–8 (5–7) have equivalent meaning, but the shocks are constructed within the median optimal event window of 50 minutes instead. Bolded columns 9–11 (8–10) are the differences between the corresponding coefficient estimates, representing the effect from event window choice.

When opening up the event window around scheduled FOMC announcements from 30 minutes to the optimal length, all monetary policy shocks that capture the effects of forward guidance have larger effects on both nominal and real interest rates. For example, increasing the event window length results in JK_{MP} to have an effect that is 26, 24, and 23 basis points larger on the 2-, 5-, and 10-year real yields measured using TIPS, respectively. The statistical significance of the coefficients at the 1% level doesn't change with the event window length. Interestingly, the target factor under the methodology of Gürkaynak, Sack, and Swanson (2005), GSS_T, has smaller coefficient estimates for nominal interest rates at all horizons when using the optimal event window length, but an unclear direction for real yields. Only estimates for the 2-year nominal yield are statistically significant when the target factor is constructed under both window lengths. One likely explanation for these results is that the full sample period includes the effective lower bound, a time period where the stimulus of monetary policy through changes in the current federal funds rate was limited and greater emphasis was put into forward guidance.

The main takeaway from the regression results of both tables is that measuring the reaction of financial markets to monetary policy announcements within too small of an event window prevents market participants from fully processing the information content of the announcements, especially those pertaining to the future path of interest rates. As a result, the effects of monetary policy shocks about forward guidance on financial market variables can become hampered. Indeed, these regression differences support an interpretation suggested by Gürkaynak, Sack, and Swanson (2005), which is that financial markets can fully react to announced changes in the federal funds rate target within a short amount of time. However, information within the FOMC statements about the outlook of policy and economic conditions are more complex and require additional time to fully process and price in by market participants.

Responses of Equities: I finish this paper with one additional piece of evidence that event window choice affects the impact of monetary policy shocks. Table 9 presents analogous results for the S&P 500 Price Index. The form of the regressions is the same as Equation 13, except the dependent variable is now 100 times the price log-difference. From the left, the second column contain estimates coming from regressions where the dependent variable is the price change in the S&P 500 Index and the independent variable is the monetary policy shock, both constructed within 30 minutes. The third column has equivalent meaning, but both variables are constructed within the median optimal event window length. The right-most column contain the differences between the corresponding coefficient estimates.

Increasing the event window around scheduled FOMC announcements from 30 minutes to the optimal length results in all monetary policy shocks containing forward guidance to have greater negative impact on stock prices. Interestingly, the larger effects of event window choice on the change in stock prices has much larger variance across the monetary policy shocks when compared to the effects seen on interest rate changes. For example, whilst opening up the event windows results in the decline S&P 500 Price Index to grow by an additional 2.69 p.p. from JK_{MP}, this decline only grows by 71 or 9 basis points when using GSS_P or NS_{MP}, respectively. Despite this heterogeneity, monetary policy shocks that incorporate information about forward guidance have larger, negative impact on stock prices when increasing the event window length from 30 to 50 minutes.

Similar to the earlier investigation on interest rates, the response of stock prices to the target factor from GSS becomes weaker by 1 p.p. when using the median optimal window length. Although the estimates are still statistically significant at the 1% level, the weaker effects are possibly due to the event window lengthening causing a "shift in importance" towards the monetary policy shock. Using the optimal window length allows more time for the stock market to fully react to the FOMC statements. As a result, market participants can quickly react to a negative shock to the current federal funds rate, then take more time to process the effects of tightening forward guidance. With regards to the central bank informational shock, one possible explanation for the difference in effects could have to do with the aforementioned combination of the larger idiosyncratic volatility of stock prices (relative to Treasury yields) and the imposed sign restrictions of JK. By expanding the event window to the median optimal length of 50 minutes, the, these two factors cause more "shifts in importance" towards central bank information shocks, amplifying the shock series in both directions. Regardless, the positive response of the S&P 500 Price Index to the shock constructed within the optimal event window is still statistically significant at the 1% level.

Overall, the heterogeneity in the differences amongst the responses of interest rates and stock prices support the findings of Brennan et al. (2024): the data on long-term rates and construction method used for monetary policy shocks are important contributors. My paper provides evidence that the dimension of event window length must also be considered. By choosing the popular 30-minute window in the literature, the effects of monetary policy shocks about forward guidance on financial variables can more or less be dampened because markets have not yet fully reacted to the policy announcements.

7 FOMC Statement Characteristics and Their Effects

Recall that systematic estimation of the event window lengths that best reflect the full reactions of markets is XLNet regressing the changes in asset prices within different windows on the text of FOMC statements. With regard to the terminology from the conceptual framework, systematic estimation could be thought of as a "joint" estimation of the signal and time horizon that best reflects the full reaction of the market to FOMC statements. However, having the neural network perform this "joint" estimation on all sample splits is computationally intensive. In particular, the financial and mandatory hardware constraints required by the neural network are why the current version of this paper only considers up to 60 minutes after the FOMC statement release for systematic estimation.

An alternative method that potentially circumvents these constraints is what I call the "one signal" approach. If the core assumption is made that the signal (i.e., predictions) from the neural network for the "jointly" estimated event window is *constant* for all time, event window lengths longer than an hour after FOMC statement release can be considered by following the conceptual framework more closely. Specifically, the "one signal" approach uses the out-of-sample predictions of all five splits from the "jointly" estimated event window and calculates the $\overline{R^2_{OOS}}$ for all event window lengths at least as long as the systematically estimated event window length. One advantage of this shortcut approach is it allows me to observe how the different dimensions of the monetary policy text potentially affect the optimal event window lengths. I then use the "one signal" approach to check if event windows beyond the optimal window length of the "jointly" estimated one have a larger $\overline{R^2_{OOS}}$.

7.1 How FOMC Statement Characteristics Affect Window Lengths

An interesting question to consider is if different aspects within the text of FOMC statements affect change the optimal event window length. I use the "one signal" approach to provide some possible insight into whether the complexity of the information content in FOMC statements, the degree of similarity between sequential statements, and the mention of dissents within the statements changes the optimal event window lengths. I note that these heterogeneity exercises rely on the core assumptions that the signal (i.e., predictions) from the neural network for the "jointly" estimated event window is *constant* for all time *and* this signal is still relevant when conditioning the FOMC statements into subsamples.[27]

Text Complexity: I first observe how the optimal event window length changes for maturities of assets conditioned on the complexity of the FOMC statement text. I assess this complexity using the standard readability formula of the Flesch-Kincaid Grade Level index.

[27] The ideal solution would be to acquire large subsamples of FOMC statements satisfying the text complexity and similarity conditions, then have XLNet systematically estimate the optimal event window lengths for all subsamples.

These readability formulas determine the grade level required for a reader to properly read and comprehend a provided text based on sentence structure (i.e., average sentence length), word structure (i.e., percentage of difficult words in a sentence), and word phonology (i.e., average number of syllables per word).[28] Figure 21 displays the evolution of the Flesch-Kincaid Grade Level for the sample period of FOMC statements. In particular, we see that the complexity of the FOMC statements under Greenspan's tenure was fairly volatile, frequently swinging between a readability level of some college and a level of 21.3, the equivalent to a doctoral level of education. Under Chair Bernanke, the grade level required to comprehend FOMC statements steadily climbed from slightly above high school to a peak reading comprehension level equivalent to a doctoral degree. The language complexity declined under both Chairs Yellen and Powell and averages between the comprehensive level of a bachelor's or master's degree level of education. Descriptive statistics for the text complexity measure can be found in Table 10.

Given that the median grade level readability of the FOMC statements is some amount of a master's level of education, I split my FOMC statements depending on whether their grade levels are below or above that threshold (i.e., 16.5). I then calculate the MSEs under the "one signal" approach for each subsample of FOMC statements for every maturity of every futures contract. A summary of this exercise is found in the first two columns of Table 11, which displays the minimised MSEs and associated event window lengths averaged across all asset types and maturities. Immediately, one can see that FOMC statements with a required readability level of at least some of a master's degree have a longer average optimal event window of 71 minutes. In contrast, "simpler" statements with a grade level up to some of a master's degree is associated with a shorter average event window length of 59 minutes. Interestingly, both subsamples of FOMC statements possess a similar MSEs on average. One potential explanation for the differences in optimal event window lengths but similar MSEs is that the "simpler" statements exhibit a relatively larger share of unrelated news, whilst

[28]For a description of U.S. education grade levels, see https://en.wikipedia.org/wiki/Education_in_the_United_States.

most of the noise in the "complicated" statements is coming from cognitive noise. Indeed, papers such as Smales and Apergis (2017) have shown that the increasing complexity of FOMC statement language over time is associated with increasing volatility across equity, bond, and currency markets. This association is consistent with the idea that more complex information results in differing interpretations and reactions to said information, therefore increasing market volatility and trading volume. In other words, financial markets might need more time to fully react to FOMC statements with more complicated language.

Text Similarity: Using the "one signal" approach, I also analyse how the optimal event window length changes when conditioned on the degree of similarity between the FOMC statements over time. The method I use for this exercise is a bag-of-words model, which represents text as an unordered, weighted-frequency of words. Importantly, this method assumes that documents with common weighted frequencies for words are discussing similar topics. By transforming the FOMC statements into vectors of word frequencies, I can perform vector analysis and create a measure of similarity between any two document vectors.

The weighted frequency of words frequently used in text analysis is called Term Frequency-Inverse Document Frequency (TFIDF). Conversion of my sample of FOMC statements into the TFIDF matrix is done through the Python text analysis library of sklearn. Specifically, each word in a document is multiplied by the number of times it occurs within a particular document over the frequency of documents where the word appears. The purpose behind this ratio is to properly weigh down the importance of frequently occurring words that don't actually provide much meaning with regard to distinguishing FOMC statements from one another. For example, words such as "a" and "the" appear in all documents with high frequency, but don't signal anything about any particular statement. Therefore, the value for these words are weighed down by the high number of occurrences across documents, yielding a *weighted frequency*. Additionally, words like "unemployment", "inflation", and "federal funds rate" will also be weighed down because monetary policy discussed in every FOMC statements has these components. However, it should be noted that these words are weighed down by a smaller degree relatively speaking because they could still convey some importance when discerning the degree of similarity between two statements (e.g., if one statement discusses about inflation relatively more than another statement that focuses more on labour market conditions). Lastly, words that do not appear in every FOMC statement, such as "persists" or "tight", are given a higher weighted frequency because they potentially signal a unique economic environment when the FOMC meeting took place compared to other meeting dates. The differences in these unique and informative words are what allow me to calculate the degree of similarity between FOMC statements.

The calculation of the TFIDF matrix is as follows: Let D be the set of FOMC statements and T be the set of all terms that appear within and across all statements in D. Let a single document and term be indexed by $d \in D, t \in T$, respectively. Therefore, the term frequency of a particular term t in document d can be defined as:

$$tf_{d,t} = \ln\left(\frac{tc_{d,t}}{nt_d}\right) + 1, \tag{9}$$

where $tc_{t,d}$ is the number of times term t appears in document d, nt_d is the total number of words in d, and both the natural logarithm and addition term serve to smooth out the frequency measure. We can then calculate the inverse document frequency as follows:

$$idf_{d,t} = \ln\left(\frac{nd}{df_{d,t} + 1}\right) + 1, \tag{10}$$

where nd is the number of documents in set D and $df_{t,d}$ is the number of documents that term t appears. Multiplying the two terms gives us the weighted frequency of each term t in document d:

$$TFIDF_{d,t} = tf_{d,t} * idf_{d,t}. \tag{11}$$

Calculating $TFIDF_{d,t} \forall d \in D, t \in T$ and combining them yields a $D \times T$ matrix, where each element $TFIDF_{d,t}$ represents the number of times a term appears in a particular document, divided by the number of words in said document, then multiplied with the document frequency (ratio between the number of documents where the term appears and the total number of documents). Essentially, the higher the TFIDF value is for a term, the more informative that word is with regard to distinguishing the information content of those FOMC statements from others.

Although the TFIDF matrix can be produced on the current version of the sample of FOMC statements, the results might not be accurate in representing the similarity of the intended or comprehended information content of the statements. For example, the method could potentially view the terms "Federal Funds Rate" and "federal funds rate" as different. In other words, this bag-of-words model is not as "sophisticated" at discerning context from the FOMC statements in their original grammatical structure compared to the neural network, which could cause the $TFIDF_{d,t}$ values to be inaccurate. To combat this issue, I employ additional preprocessing steps on my sample of FOMC statements. First, I make every word lowercase. Second, I remove common words that convey little semantic meaning, such as articles, pronouns, and conjunctions.[29] The last step involves converting all words into their "base" form (e.g., the words "increases", "increasing", and "increase" are all combined into the base form of "increas"). Calculating the TFIDF matrix on the sample of additionally cleaned FOMC statements from May 1999 through October 2019 yields a matrix with 165 rows (statements) and 966 columns (terms). Table 12 presents a list of 30 base terms that have the highest TFIDF scores for my sample of FOMC statements. Recall that terms with higher TFIDF values are more informative terms with regard to differentiating the FOMC statements with them from statements without.

With the TFIDF matrix calculated, I am able to produce a corresponding matrix whose values represent a measure of similarity between any two pairs of FOMC statements. Specifically, this document similarity matrix is created by multiplying the TFIDF matrix with its

[29] I choose to retain dates and numbers because the FOMC's targetted federal funds rate or discussions about date-based forward guidance convey important semantic content.

transpose:

$$\text{Document Similarity Matrix} = TFIDF \cdot TFIDF^T. \tag{12}$$

To understand the document similarity matrix, consider a document d row vector of the TFIDF matrix. For each term $t \in T$, the $TFIDF_{d,t}$ values are only positive if the terms appear in document d, otherwise the value is zero. Additionally, the vectors for every document all have the same magnitude due to normalisation by the number of documents and terms in the matrix. Because the product between the TFIDF matrix and its transpose is essentially the dot product between every pair of document row vectors in the sample of FOMC statements. As a result, we can define the degree of similarity between any two FOMC statements as the cosine of the angle between these documents, also called the *cosine similarity*:

$$S^{A,B} := \cos\theta = \frac{\mathbf{A} \cdot \mathbf{B}}{\|\mathbf{A}\|\|\mathbf{B}\|}, \tag{13}$$

where $\mathbf{A}, \mathbf{B}$ are the vectors for FOMC statements A and B, respectively. The more similar two FOMC statements are, the angle between the two corresponding vectors approaches zero, resulting in the cosine of the angle to go to one. A cosine similarity value of one between two FOMC statements means they are identical, whilst a value of zero means the two documents have no common words. In other words, the more base terms shared between two FOMC statements, the higher cosine similarity value is assigned to the pair.

The Document Similarity Matrix for FOMC statements from May 1999 through October 2019 is represented as a heat map in Figure 22. The rows and columns are FOMC statements ordered by release statement, top-to-bottom and left-to-right, respectively. For any FOMC statement in row d and another statement in column d', the element (d, d') represents the cosine similarity measure between the pair of statements. Elements coded as darker (lighter) shades of blue (green) represent higher (lower) similarity values. The main diagonal of the matrix is a diagonal of ones (i.e., the darkest shade of blue) because the cosine similarity measure is calculated between an FOMC statement with itself. Moving away from the main diagonal represents a comparison between FOMC statements with other statements over time. An interesting pattern seen throughout the heat map is that FOMC statements have become increasingly similar over time, represented by the increasing area of shades of blue when moving from the top-left to the bottom-right corners. The increased persistence and standardisation of FOMC statement wording begins roughly between early-2009 and early-2010, which coincides with the period when the FOMC was in the process of reducing the federal funds rate towards the zero lower bound. As discussed in Handlan (2022a), one explanation behind this occurrence is that the FOMC wanted to avoid market surprises through reducing the variation in statement vocabulary after the financial crisis. Even when the zero lower bound ended with the Board raising the federal funds rate at the end of 2015, the cosine similarity measures remained high through 2019 (represented by the dark blue shadings), possibly due to the efforts of the FOMC to increase the transparency of its monetary policy under Chairs Yellen and Powell.

The series of document-pairs $(d, d-1)$ represents the degree of similarity between sequential FOMC statements, which I call as S^1 for the rest of the paper and is plotted in Figure 23. Similar to the colour trend observed in the heat map, as time progresses, the cosine similarity between sequential FOMC statements increases. Descriptive statistics for S^1 can be found in Table 5.

I split my FOMC statements depending on whether S^1 value is below or above the median (i.e., 0.88), labelling the subsample of statements as being "different" or "similar" relative to their immediately previous document, respectively. Calculating the MSEs for each subsample of FOMC statements for every maturity of every asset, I present the results of this exercise in the third and fourth columns from the left of Table 11. "Different" FOMC statements observe the smallest MSEs within an event window length of 61 minutes when averaged across all asset types and maturities, whilst "similar" statements see minimised MSEs within a 51-minute window on average. Similar to the condition of text complexity, both subsets of statements have similar minimised MSEs on average. These results with respect to cosine similarity could be due to the presence of unrelated news and cognitive noise: the noise affecting financial market reactions to "simpler" statements is comprised relatively more of unrelated news, shortening the amount of time required to fundamentally react to the information context. In contrast, cognitive noise is the larger contributor when reacting to "different" statements. Intuitively, if an FOMC statement contains less similar base terms and associated ideas with its predecessor, financial markets could require more time in order to discern and react to the new information of the current FOMC statement. Conversely, markets would presumably react to statements that share a lot of terms and concepts with past policy announcements in a short amount of time because most of said information has already been incorporated into the price.

Presence of Dissents: The final characteristic of the FOMC statements I consider under the "one signal" approach is whether the presence of dissents in the monetary policy announcements affects the optimal event window lengths of asset types. Roughly 40% of FOMC statements in my sample have recorded dissents, a share similar to that found in prior studies. While this suggests dissents are not rare, they still provide important signals. According to Federal Reserve tradition, dissents are usually recorded only when Board members find the majority's opinion unacceptable (C Madeira and J Madeira, 2019). In other words, the very existence of a recorded dissent provides additional information for markets to process, which in turn could affect their reaction time. To investigate this characteristic, I split my sample of FOMC statements depending on whether the policy votes were unanimous or not.[30] The fifth and sixth columns of Table 11 present the calculated MSEs for each subset of statements. On average, statements with(out) dissents observe the smallest MSE under the "one signal" approach within an event window length of 83 (61) minutes. The longer reaction time for statements with dissents may be because they introduce additional layers of information regarding policy transparency and internal disagreement, requiring more time for markets to process compared to the unanimous announcements.

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

7.2 Optimal Event Window Lengths Beyond 70 Minutes?

I also employ the "one signal" approach to check if event windows beyond the optimal window length of the "jointly" estimated one have a larger $\overline{R^2_{OOS}}$. Figures 24–25 visually display the results of this exercise for maturities of federal funds futures, Eurodollar futures, Treasury futures of two, five, ten, and thirty years, and both the S&P 500 Index and its E-mini futures, respectively. The horizontal axis depicts the event window lengths, starting from the systematically estimated event window length and ending at an event window starting 10 minutes before and ending 18 hours after FOMC statement release. The cross points represent the event window length associated with the highest $\overline{R^2_{OOS}}$. One can see that for most maturities and assets, the event window length with the largest $\overline{R^2_{OOS}}$ is the length systematically estimated by the "joint" approach. In other words, the results from this exercise can be viewed as a robustness check in support of XLNet providing a "good" signal overall for systematic event window length estimation. Although these results may seem trivial, recall that neural networks such as XLNet are non-linear models whose weights and embeddings are sensitive to changes in both the output and input variables of asset price log-differences and FOMC statements, respectively. When combined with the fact that the signal can change with the event window length used to calculate the price log-differences, it is entirely possible that the systematically estimated event window is different from that which has the largest $\overline{R^2_{OOS}}$ under the "one signal" approach.[31] As an example, consider how the "one signal" approach estimates that the optimal event window length for 1-month-ahead federal fund futures ($FF2$), 3-month-ahead federal fund futures $FF4$), front-month 2-year Treasury futures ($TUc1$), second-month 10-year Treasury futures ($TYc2$), and front-month 30-year Treasury futures ($USc1$) should be 1080, 300, 130, 360, and 330 minutes, respectively. To confirm the validity of these estimated window lengths, I calculate $\overline{R^2_{OOS}}$ under the "joint" approach for these futures. The results are depicted as the rightmost box-and-whisker plot in the respective sub-figures of systematic estimation for these futures

[31] A rough analogy is how iterative generalised method of moments does not always not converge.

contracts. Two insights can be taken away from this robustness exercise. First, the optimal event window for these futures contracts is still within 60 minutes in length. However, "joint" estimation for all these markets showed that the considered window lengths beyond 60 minutes after statement released yielded $\overline{R^2_{OOS}}$ greater than that obtained within a 30-minute window. This leads to the second insight, which is the interesting possibility that the global optimal event window length might possibly be between 60 minutes and the amount of time predicted by the "one signal" approach after FOMC statement release. Regardless, a 30-minute window is never predicted to be the optimal length.

8 Conclusion

The choice of event window length for measuring financial market responses to news has largely remained an "ad-hoc" decision in the empirical monetary policy literature. This paper challenges the conventions that have emerged from this practice by asking a crucial question: how does one choose the appropriate event window length for their study in monetary policy? By combining observed price dynamics with a text-based signal derived using neural networks methods for text analysis, I develop and implement a methodology to systematically estimate the event window lengths that best reflect the full market reaction to the information content of FOMC statements.

This paper's systematic estimation yields two key findings that directly confront the common assumptions in the literature. First, the common 30-minute window is insufficient time for markets to fully react to FOMC announcements. My results show that, on average, markets fully react within an event window *ending at least 30 minutes after release*, corresponding to a total window length of at least 40 minutes. A 30-minute window is never found to be optimal for any asset type considered. Second, the optimal window length is not a universal parameter. In line with this paper's title, one window does not fit all; the optimal duration increases systematically with asset time horizon. This estimated length rises from 40 minutes for assets with the shortest time horizons to 50-60 minutes for futures with time horizons of two quarters or more. Relatedly, statements with greater complexity, less similarity, and the presence of dissents are associated with longer event windows on average.

The implications of these findings are not merely methodological, as the choice of event window has a tangible impact on the construction and interpretation of monetary policy surprises and shocks. I document that the correlation between surprises measured within the optimal windows and those from a conventional 30-minute window decreases with asset time horizon. These discrepancies are economically meaningful, resulting in observed differences in derived monetary policy shocks, particularly the forward guidance component. Furthermore, the responses of nominal and real interest rates to monetary policy shocks about forward guidance become larger when opening up the event window to the optimal length. This larger estimated impact is accompanied by an increase or no change in its precision, suggesting that shorter, conventional windows attenuate the measured effects of policy. Similar results are found in the response of stock prices to these shock series.

Ultimately, this paper argues that determining the optimal event window length is an empirical question, not a parameter whose value should be simply assumed. The provided methodology offers a systematic approach for this basic but critical step in event window studies. The results indicate that by allowing for longer, asset-specific reaction times, we can construct monetary policy surprises that more accurately reflect the market's full response to central bank communication, leading to a more precise understanding of the effects of monetary policy. Indeed, as the literature considers broader measures of central bank communication in order to construct more holistic monetary policy shocks, as in Neuhierl and Weber (2019), Swanson and Jayawickrema (2023), and Bauer and Swanson (2023), I argue that when the primary source of reaction is communicated through text, the methodology of this paper can be used to measure when markets fully react to these policy communication.

References

Acosta, Miguel (2023). "The Perceived Causes of Monetary Policy Surprises". Published manuscript.

Acosta, Miguel, Connor M. Brennan, and Margaret M. Jacobson (2024). *Constructing high-frequency monetary policy surprises from SOFR futures*. Tech. rep. Finance and Economics Discussion Series 2024-034. Board of Governors of the Federal Reserve System.

An, Phillip, Karlye Dilts Stedman, and Amaze Lusompa (2025). *How High Does High Frequency Need to Be? A Comparison of Daily and Intradaily Monetary Policy Surprises*. Tech. rep. Research Working Paper no. 25-03. Federal Reserve Bank of Kansas City.

Athey, Susan and Guido Imbens (2019). *Machine Learning Methods Economists Should Know About*.

Bauer, Michael D., Aeimit Lakdawala, and Philippe Mueller (2022). "Market-Based Monetary Policy Uncertainty". In: *The Economic Journal* 132.644, pp. 1290–1308.

Bauer, Michael D. and Eric T. Swanson (2023). "A Reassessment of Monetary Policy Surprises and High-Frequency Identification". In: *NBER Macroeconomics Annual* 37.1, pp. 87–155.

Bazzana, Flavio and Andrea Collini (2020). "How does HFT activity impact market volatility and the bid-ask spread after an exogenous shock? An empirical analysis on S&P 500 ETF". In: *The North American Journal of Economics and Finance* 54, p. 101240.

Ben Ammar, Imen and Slaheddine Hellara (2022). "High-frequency trading, stock volatility, and intraday crashes". In: *The Quarterly Review of Economics and Finance* 84, pp. 337–344.

Ben-David, Itzhak, Francesco Franzoni, Byungwook Kim, and Rabih Moussawi (2022). "Competition for Attention in the ETF Space". In: *The Review of Financial Studies* 36.3, pp. 987–1042.

Bianchi, Francesco, Sydney C Ludvigson, and Sai Ma (2024). *What Hundreds of Economic News Events Say About Belief Overreaction in the Stock Market*. Working Paper 32301. National Bureau of Economic Research.

Boehm, Christoph E and T Niklas Kroner (2025a). "Monetary Policy without Moving Interest Rates: The Fed Non-Yield Shock". SSRN Working Paper No 3812524.

Boehm, Christoph E and T Niklas Kroner (2025b). "The U.S., Economic News, and the Global Financial Cycle". In: *The Review of Economic Studies*, rdaf020.

Boguth, Oliver, Adlai J. Fisher, Vincent Gregoire, and Charles Martineau (2023). "Noisy FOMC Returns? Information, Price Pressure, and Post-Announcement Reversals". SSRN Working Paper No 878091.

Bordalo, Pedro, Nicola Gennaioli, Rafael La Porta, and Andrei Shleifer (2024). "Belief Overreaction and Stock Market Puzzles". In: *Journal of Political Economy* 132.5, pp. 1450–1484.

Brennan, Connor M., Margaret M. Jacobson, Christian Matthes, and Todd B. Walker (2024). *Monetary Policy Shocks: Data or Methods?* Tech. rep. Finance and Economics Discussion Series 2024-011r1. Board of Governors of the Federal Reserve System.

Brooks, Jordan, Michael Katz, and Hanno Lustig (2023). *Post-FOMC Announcement Drifts in U.S. Bond Markets*. Working Paper 25127. National Bureau of Economic Research.

Chang, Son J and Son-Nan Chen (1989). "Stock-price adjustment to earnings and dividend surprises". In: *Quarterly Review of Economics and Business* 29.1, pp. 68–81.

Crump, Richard K., Stefano Eusepi, and Emanuel Moench (2013). *Making a Statement: How Did Professional Forecasters React to the August 2011 FOMC Statement?* Liberty Street Economics 20130107. Federal Reserve Bank of New York.

Das, Somnath and Alexander Z. King (2021). "Measuring the informativeness of earnings announcements: The role of event windows". In: *The Quarterly Review of Economics and Finance* 82, pp. 350–367.

Doh, Taeyoung, Dongho Song, and Shu-Kuei Yang (2023). "Deciphering Federal Reserve Communication via Text Analysis of Alternative FOMC Statements". Federal Reserve Bank of Kansa City Working Paper.

Duffee, Gregory (2013). "Forecasting Interest Rates". In: *Handbook of Economic Forecasting*. Ed. by Graham Elliott and Allan Timmermann. Vol. 2. Handbook of Economic Forecasting. Elsevier. Chap. 7, pp. 385–426.

Gentzkow, Matthew, Bryan Kelly, and Matt Taddy (2019). "Text as Data". In: *Journal of Economic Literature* 57.3, pp. 535–74.

Gertler, Mark and Peter Karadi (2015). "Monetary Policy Surprises, Credit Costs, and Economic Activity". In: *American Economic Journal: Macroeconomics* 1, pp. 44–76.

Glasserman, Paul and Caden Lin (2023). *Assessing Look-Ahead Bias in Stock Return Predictions Generated By GPT Sentiment Analysis*.

Golez, Benjamin, Peter Kelly, and Ben Matthies (2025). "FOMC News and Segmented Markets". In: *Journal of Accounting and Economics* 79.2, p. 101767.

Graham, Benjamin (1974). *The Renaissance of Value: The Proceedings of a Seminar on the Economy, Interest Rates, Portfolio Management, and Bonds Vs Common Stocks, September 18, 1974*. Financial Analysts Research Foundation.

Gürkaynak, Refet S., Burçin Kisacikoğlu, and Jonathan H. Wright (2020). "Missing Events in Event Studies: Identifying the Effects of Partially Measured News Surprises". In: *American Economic Review* 110.12, pp. 3871–3912.

Gürkaynak, Refet S., Brian Sack, and Eric T. Swanson (2005). "Do Actions Speak Louder Than Words? The Response of Asset Prices to Monetary Policy Actions and Statements". In: *International Journal of Central Banking* 1.1.

Gürkaynak, Refet S., Brian Sack, and Jonathan H. Wright (2010). "The TIPS Yield Curve and Inflation Compensation". In: *American Economic Journal: Macroeconomics* 2.1, pp. 70–92.

Handlan, Amy (2022a). "FedSpeak Matters: Statement Similarity and Monetary Policy Expectations". Published manuscript.

Handlan, Amy (2022b). "Text Shocks and Monetary Surprises: Text Analysis of FOMC Statements with Machine Learning". Published manuscript.

Hawinkel, Stijn, Willem Waegeman, and Steven Maere (2024). "Out-of-Sample R2: Estimation and Inference". In: *The American Statistician* 78.1, pp. 15–25.

Hervé, Fabrice, Mohamed Zouaoui, and Bertrand Belvaux (2019). "Noise traders and smart money: Evidence from online searches". In: *Economic Modelling* 83, pp. 141–149.

Hillmer, S.C. and P.L. Yu (1979). "The market speed of adjustment to new information". In: *Journal of Financial Economics* 7.4, pp. 321–345.

Husted, Lucas, John Rogers, and Bo Sun (2020). “Monetary policy uncertainty”. In: *Journal of Monetary Economics* 115, pp. 20–36.

Jarociński, Marek and Peter Karadi (2020). “Deconstructing Monetary Policy Surprises—The Role of Information Shocks”. In: *American Economic Journal: Macroeconomics* 12.2, pp. 1–43.

Krivin, Dmitry, Robert Patton, Erica Rose, and David Tabak (2003). “Determination of the Appropriate Event Window Length in Individual Stock Event Studies”. SSRN Working Paper No 466161.

Kuttner, Kenneth N. (2001). “Monetary Policy Surprises and Interest Rates: Evidence from the Fed Funds Futures Market”. In: *Journal of Monetary Economics* 47.3, pp. 523–544.

Madeira, Carlos and João Madeira (2019). “The Effect of FOMC Votes on Financial Markets”. In: *The Review of Economics and Statistics* 101.5, pp. 921–932.

Miranda-Agrippino, Silvia and Giovanni Ricco (2021). “The Transmission of Monetary Policy Shocks”. In: *American Economic Journal: Macroeconomics* 13.3, pp. 74–107.

Nakamura, Emi and Jón Steinsson (2018). “High-Frequency Identification of Monetary Non-Neutrality: The Information Effect”. In: *The Quarterly Journal of Economics* 133.3, pp. 1283–1330.

Neuhierl, Andreas and Michael Weber (2019). “Monetary policy communication, policy slope, and the stock market”. In: *Journal of Monetary Economics* 108. “Central Bank Communications:From Mystery to Transparency”May 23-24, 2019Annual Research Conference ofthe National Bank of UkraineOrganized in cooperation withNarodowy Bank Polski, pp. 140–155.

Neuhierl, Andreas and Michael Weber (2024). *Monetary Momentum.* Chicago Booth Research Paper, Fama-Miller Working Paper, University of Chicago, Becker Friedman Institute for Economics Working Paper, LawFin Working Paper 20-05, 2020-39, 37. Chicago Booth Research Paper Series, Chicago Booth: Fama-Miller Working Paper Series, Becker Friedman Institute for Economics Working Paper Series, DFG Center for Advanced Studies - Foundations of Law and Finance.

Okada, Masayuki (2025). “Interest Rate Risk around Monetary Policy Announcements and Asset Duration”. Working paper.

Piazzesi, Monika and Eric T. Swanson (2008). “Futures prices as risk-adjusted forecasts of monetary policy”. In: *Journal of Monetary Economics* 55.4, pp. 677–691.

Piller, Alexander, Marc Schranz, and Larissa Schwaller (2025). “Using Natural Language Processing to Identify Monetary Policy Shocks”. Working Paper.

Rajapakse, Thilina C., Andrew Yates, and Maarten de Rijke (2024). “Simple Transformers: Open-source for All”. In: *Proceedings of the 2024 Annual International ACM SIGIR Conference on Research and Development in Information Retrieval in the Asia Pacific Region.* SIGIR-AP 2024. Tokyo, Japan, pp. 209–215.

Ramey, V.A. (2016). “Chapter 2 - Macroeconomic Shocks and Their Propagation”. In: *Handbook of Macroeconomics.* Ed. by John B. Taylor and Harald Uhlig. Vol. 2. Elsevier, pp. 71–162.

Rigobon, Roberto and Brian Sack (2004). “The Impact of Monetary Policy on Asset Prices”. In: *Journal of Monetary Economics* 51.8, pp. 1553–1575.

Sarkar, Suproteem and Keyon Vafa (2024). “Lookahead Bias in Pretrained Language Models”. SSRN Working Paper No 4754678.

Smales, L.A. and N. Apergis (2017). “Does more complex language in FOMC decisions impact financial markets?” In: *Journal of International Financial Markets, Institutions and Money* 51, pp. 171–189.

Swanson, Eric T. and Vishuddhi Jayawickrema (2023). “Speeches by the Fed Chair Are More Important than FOMC Announcenments: An Improved High-Frequency Measure of U.S. Monetary Policy Shocks”. Unpublished manuscript.

Vaswani, Ashish, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N. Gomez, Lukasz Kaiser, and Illia Polosukhin (2017). “Attention Is All You Need”. In: *CoRR* abs/1706.03762.

Yang, Zhilin, Zihang Dai, Yiming Yang, Jaime G. Carbonell, Ruslan Salakhutdinov, and Quoc V. Le (2019). “XLNet: Generalized Autoregressive Pretraining for Language Understanding”. In: *CoRR* abs/1906.08237.

Figures

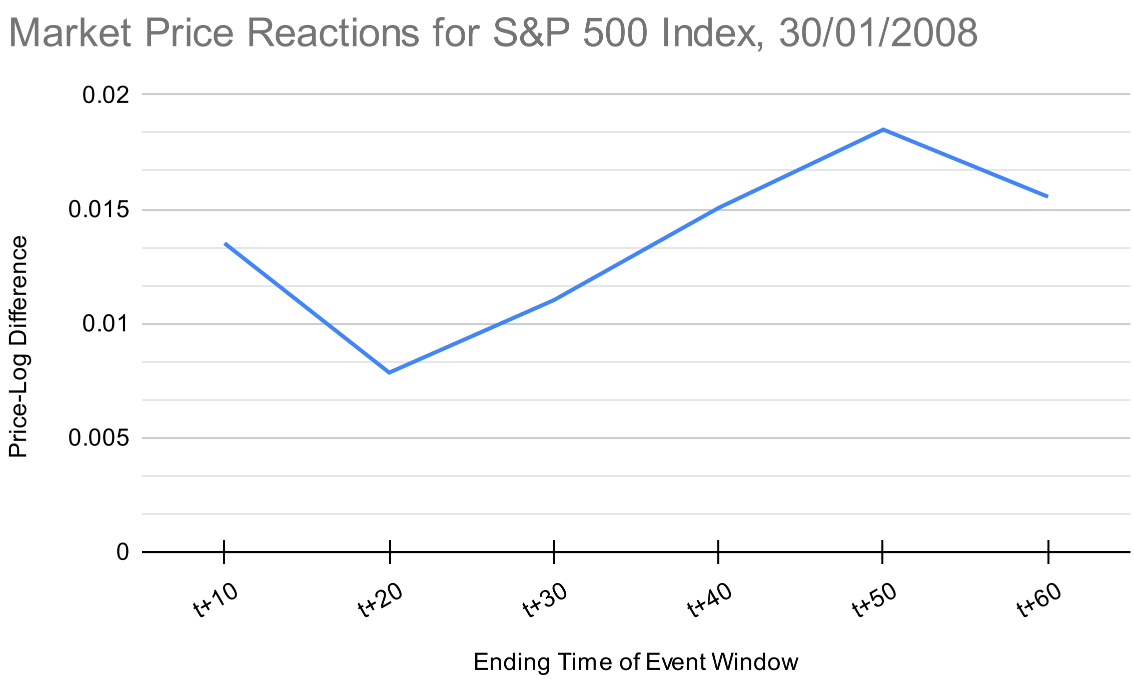


Figure 1: Responses of S&P 500 Index Market to FOMC Statements

Notes: The price log-differences of the S&P 500 Index market for different event window lengths after the release of the 30 January, 2008 FOMC statement is depicted. The horizontal axis of each figure depicts the end time of the considered event window lengths and the vertical axis represents the price-log differences.

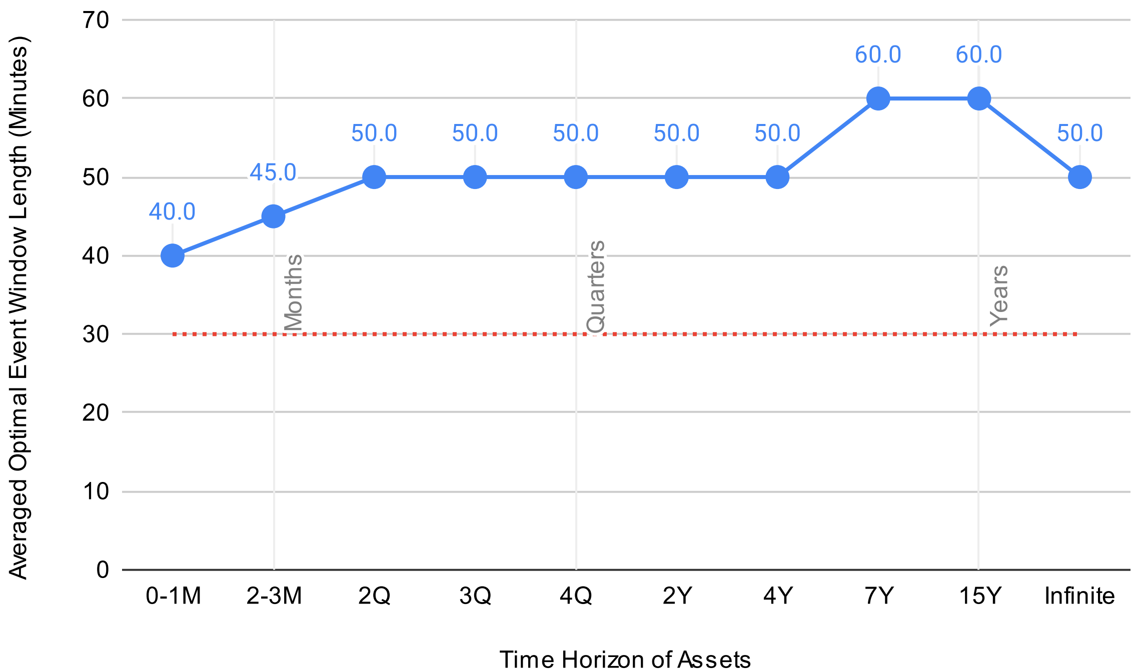


Figure 2: Averaged Optimal Event Window Lengths for Various Asset Time Horizons

Notes: The horizontal axis depicts the horizons of all considered futures contracts and equities. The vertical axis depicts the event window lengths in minutes, with all windows starting at 10 minutes before FOMC statement release. The red dotted line depicts the 30-minute window length, common in the literature. The systematically estimated event window lengths are averaged across futures maturities for each asset type. "0–1M" is the average of the event window lengths for front-month and 1-month-ahead Federal Funds futures. "2–3M" is the average of the event window lengths for 2-month and 3-month-ahead Federal Funds futures. "Infinite" is the time horizon of the S&P 500 Index and considered E-mini futures contracts. The time horizons for the Treasury futures contracts are approximated by Gürkaynak, Kisacikoğlu, et al. (2020).

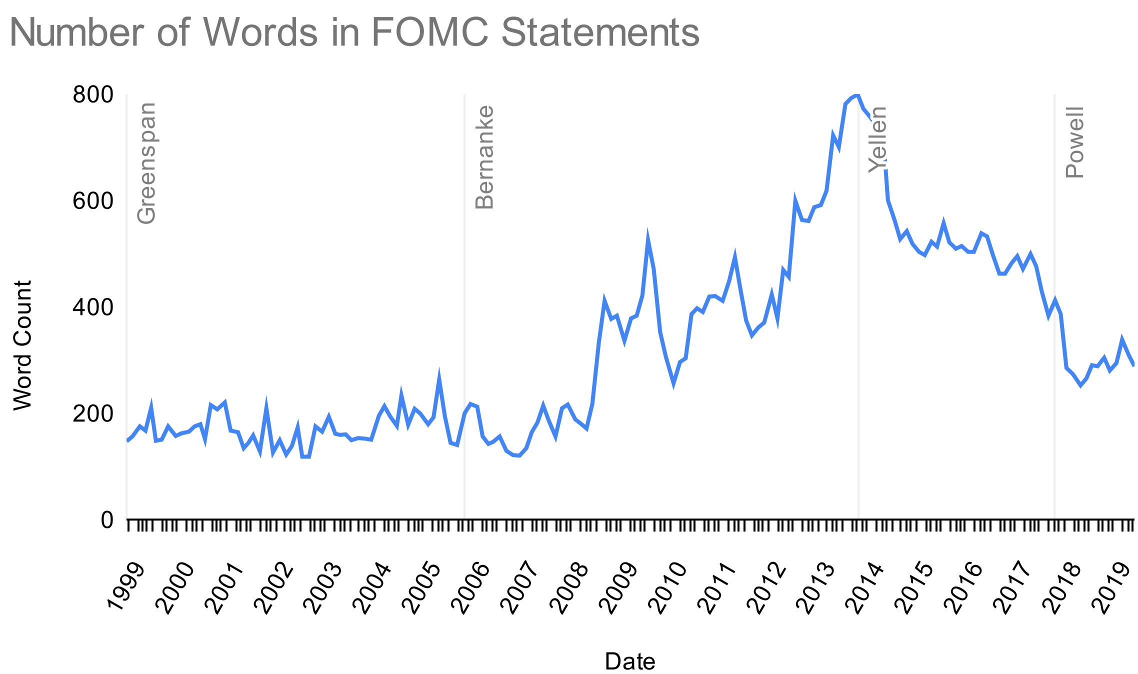
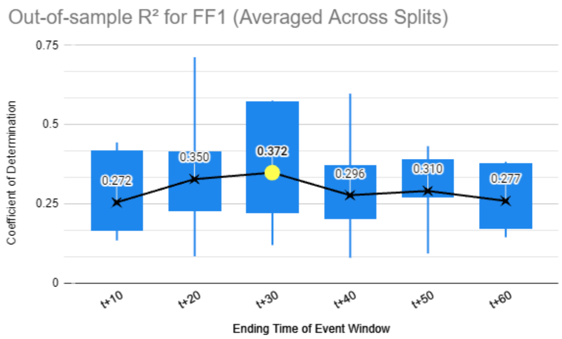
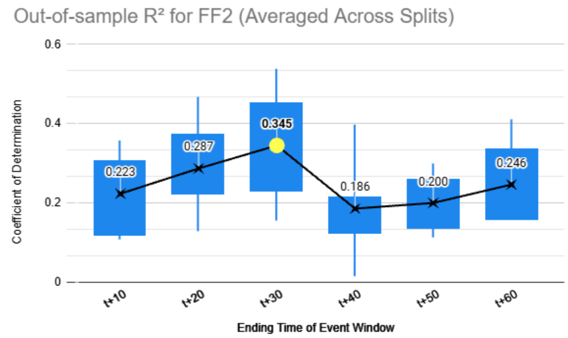


Figure 3: Number of Words in FOMC Statements, May 1999–October 2019

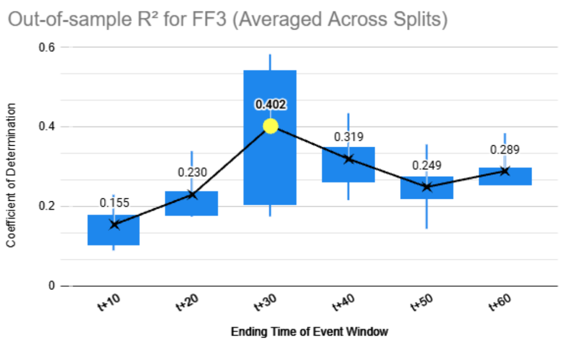
Notes: The above counts are for FOMC statements that have underwent pre-processing, which is explained in Subsection 3.1. From left to right, the vertical grey lines indicate the first FOMC meeting with Greenspan, Bernanke, Yellen, and Powell as Fed Chair.



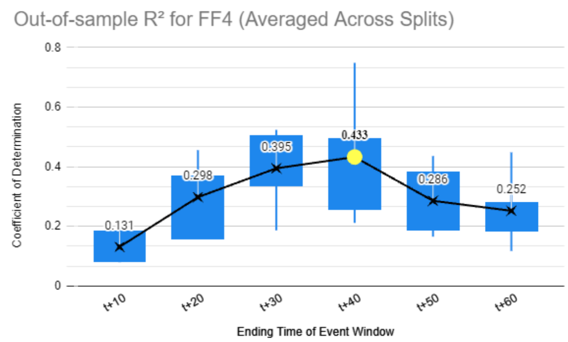
(a) $FF1$



(b) $FF2$

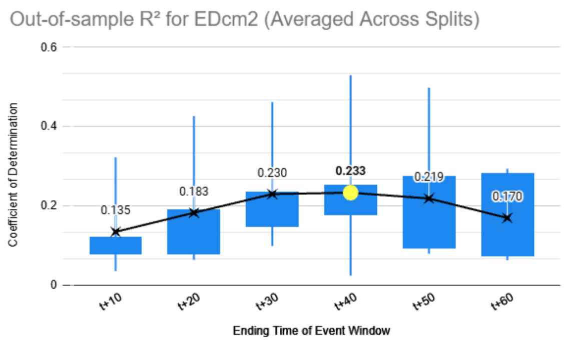


(c) $FF3$

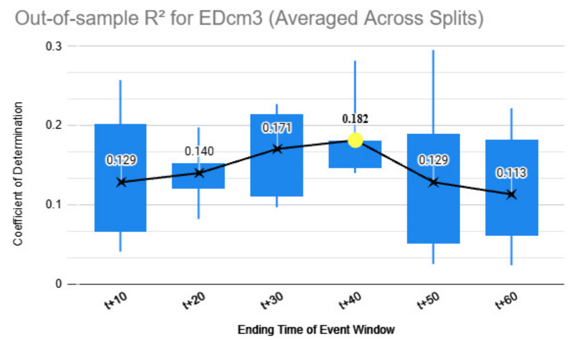


(d) $FF4$

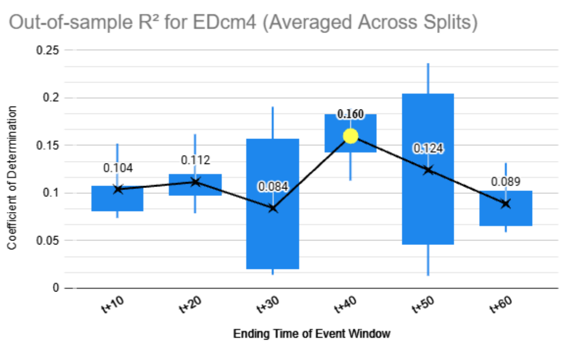
Figure 4: Systematic Estimation of Optimal Window Sizes for Federal Funds Futures
Notes: The horizontal axis of each figure depicts the end time of the considered event window lengths and the vertical axis represents the percentage points of price changes by the market directly and only due to the FOMC statement text. The cross points represent $\overline{R^2_{OOS}}$ for each event window size, where the solid yellow point represents the event window with the largest $\overline{R^2_{OOS}}$. For each event window, box-and-whisker plots are shown surrounding the corresponding averages. $0 \leq \overline{R^2_{OOS}} \leq 1$ represents the proportion of the mean squared error from predicting with the in-sample average explained by the superior out-of-sample performance of XLNet.



(a) $EDcm2$



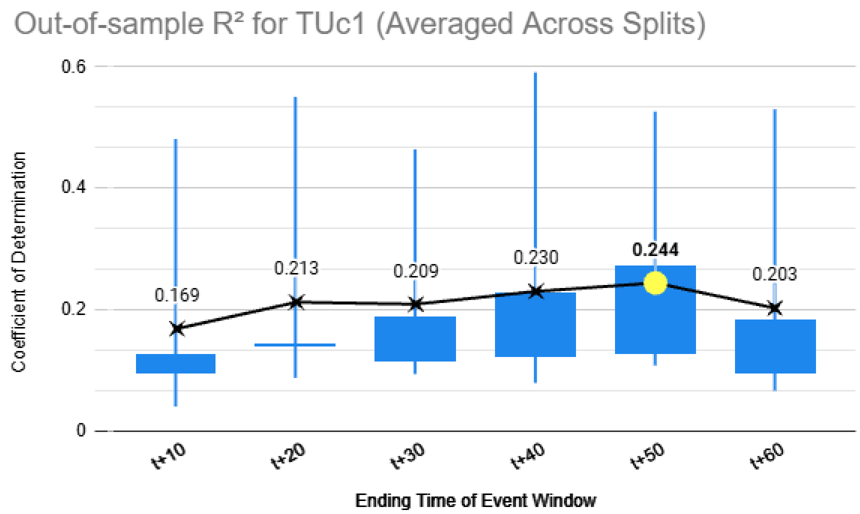
(b) $EDcm3$



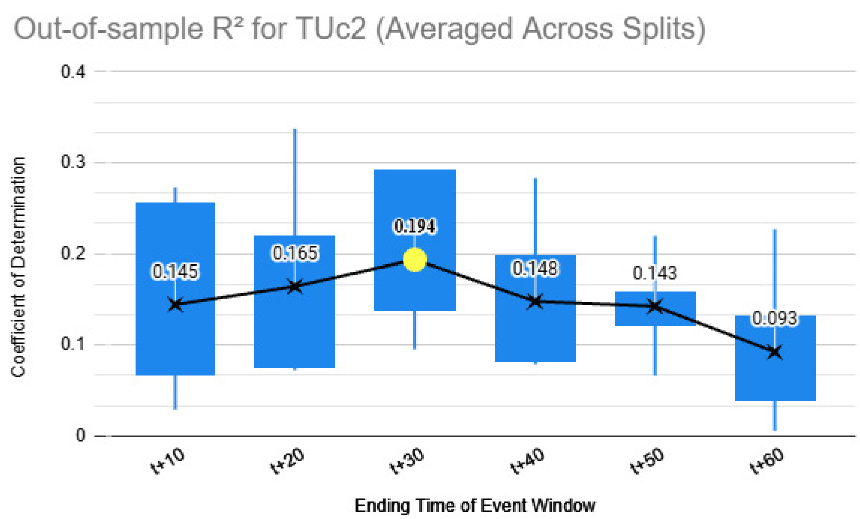
(c) $EDcm4$

Figure 5: Systematic Estimation of Optimal Window Sizes for Eurodollar Futures

Notes: The horizontal axis of each figure depicts the end time of the considered event window lengths and the vertical axis represents the percentage points of price changes by the market directly and only due to the FOMC statement text. The cross points represent $\overline{R^2_{OOS}}$ for each event window size, where the solid yellow point represents the event window with the largest $\overline{R^2_{OOS}}$. For each event window, box-and-whisker plots are shown surrounding the corresponding averages. $0 \leq \overline{R^2_{OOS}} \leq 1$ represents the proportion of the mean squared error from predicting with the in-sample average explained by the superior out-of-sample performance of XLNet.



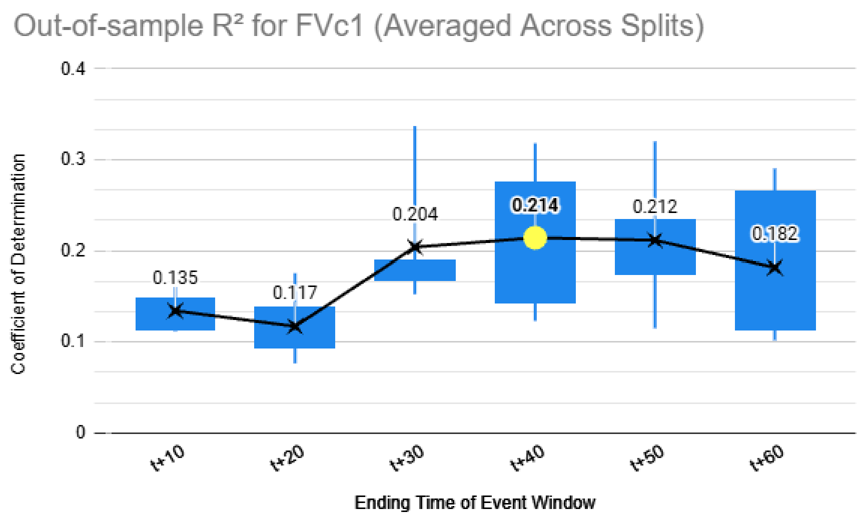
(a) $TUc1$



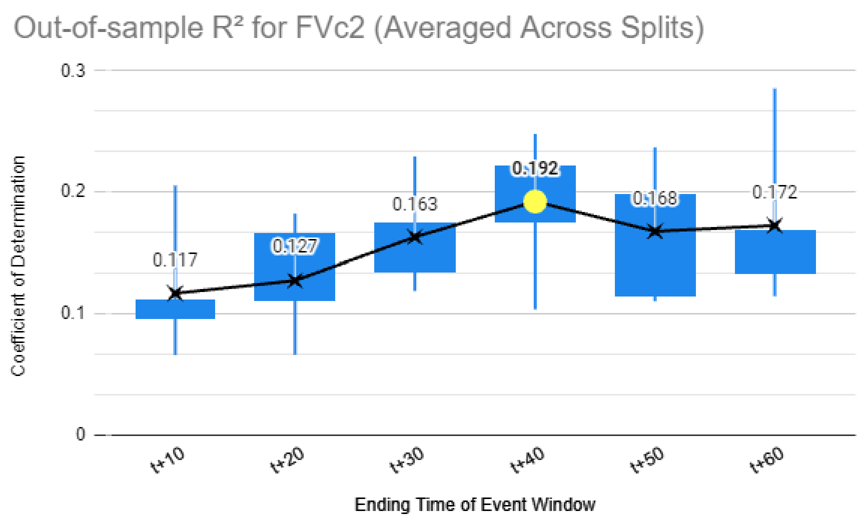
(b) $TUc2$

Figure 6: Systematic Estimation of Optimal Window Sizes for 2-Year Treasury Futures

Notes: The horizontal axis of each figure depicts the end time of the considered event window lengths and the vertical axis represents the percentage points of price changes by the market directly and only due to the FOMC statement text. The cross points represent $\overline{R^2_{OOS}}$ for each event window size, where the solid yellow point represents the event window with the largest $\overline{R^2_{OOS}}$. For each event window, box-and-whisker plots are shown surrounding the corresponding averages. $0 \leq \overline{R^2_{OOS}} \leq 1$ represents the proportion of the mean squared error from predicting with the in-sample average explained by the superior out-of-sample performance of XLNet.

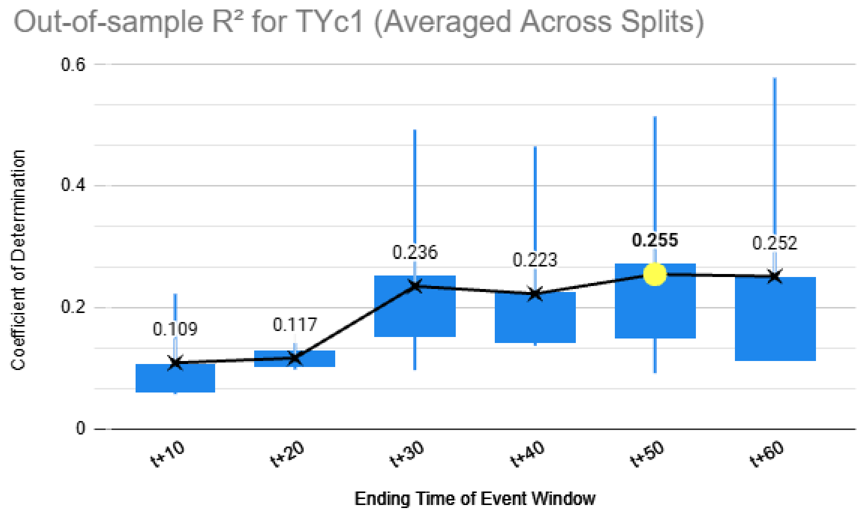


(a) $FVc1$

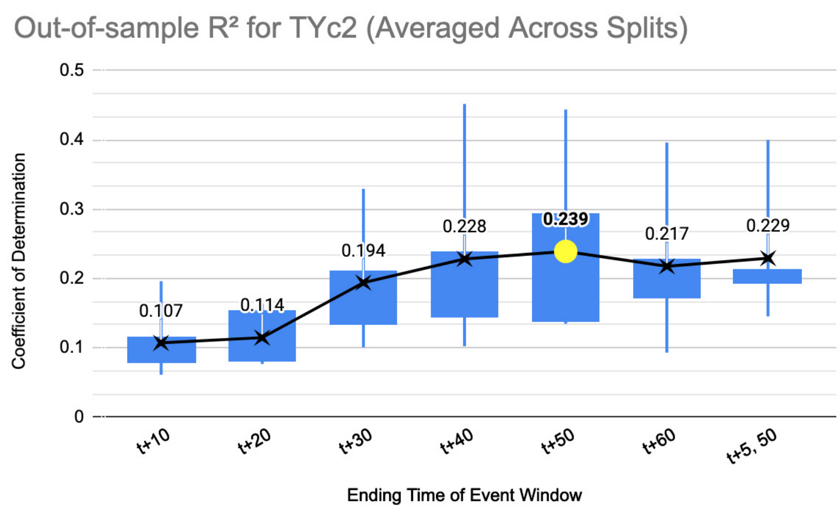


(b) $FVc2$

Figure 7: Systematic Estimation of Optimal Window Sizes for 5-Year Treasury Futures
Notes: The horizontal axis of each figure depicts the end time of the considered event window lengths and the vertical axis represents the percentage points of price changes by the market directly and only due to the FOMC statement text. The cross points represent $\overline{R^2_{OOS}}$ for each event window size, where the solid yellow point represents the event window with the largest $\overline{R^2_{OOS}}$. For each event window, box-and-whisker plots are shown surrounding the corresponding averages. $0 \leq \overline{R^2_{OOS}} \leq 1$ represents the proportion of the mean squared error from predicting with the in-sample average explained by the superior out-of-sample performance of XLNet.

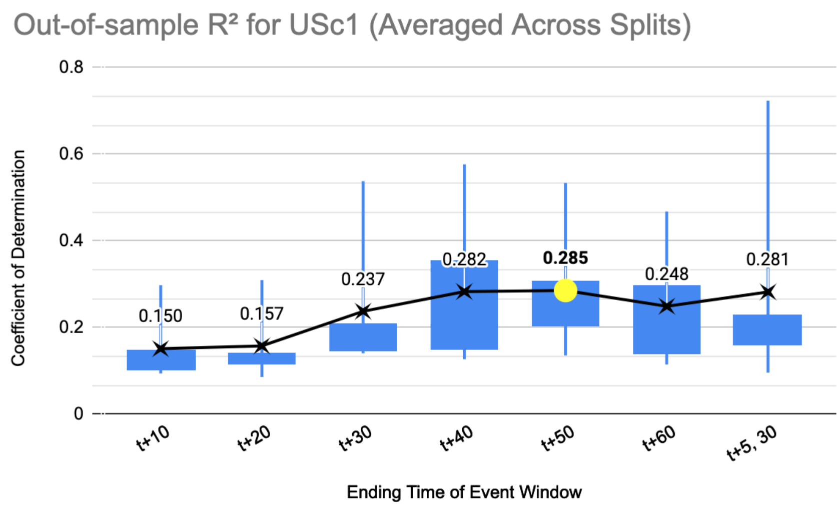


(a) $TYc1$

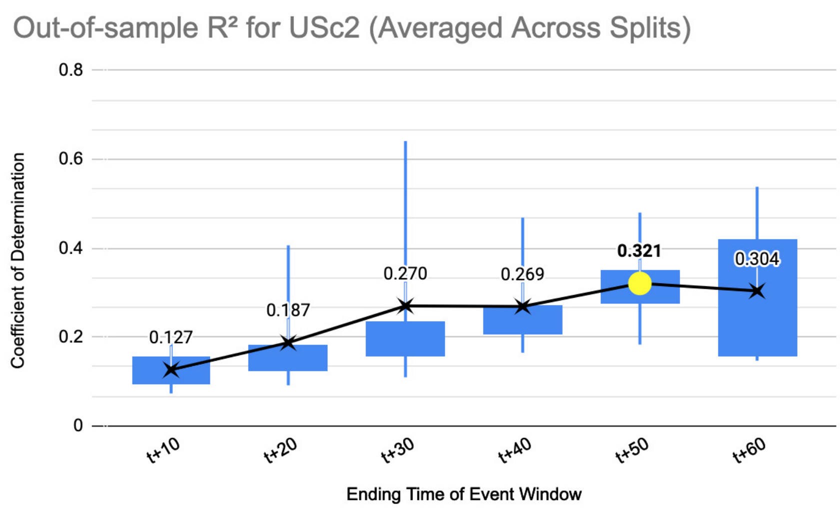


(b) $TYc2$

Figure 8: Systematic Estimation of Optimal Window Sizes for 10-Year Treasury Futures
Notes: The horizontal axis of each figure depicts the end time of the considered event window lengths and the vertical axis represents the percentage points of price changes by the market directly and only due to the FOMC statement text. The cross points represent $\overline{R^2_{OOS}}$ for each event window size, where the solid yellow point represents the event window with the largest $\overline{R^2_{OOS}}$. For each event window, box-and-whisker plots are shown surrounding the corresponding averages. $0 \leq \overline{R^2_{OOS}} \leq 1$ represents the proportion of the mean squared error from predicting with the in-sample average explained by the superior out-of-sample performance of XLNet.

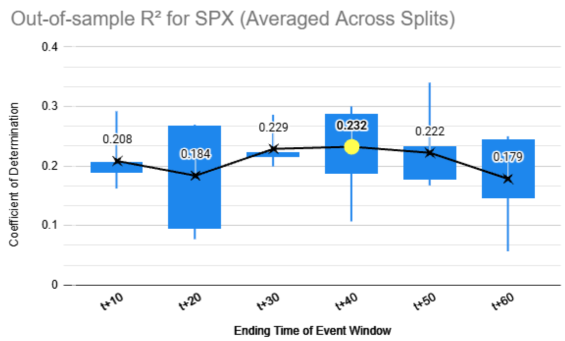


(a) $USc1$

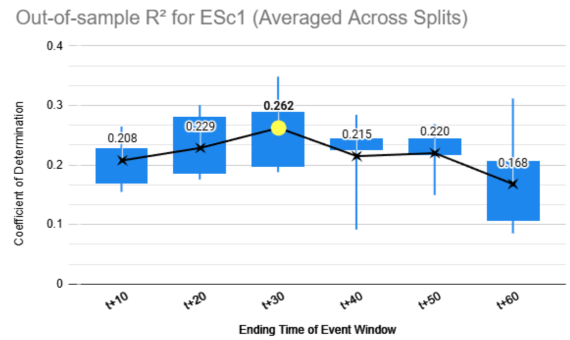


(b) $USc2$

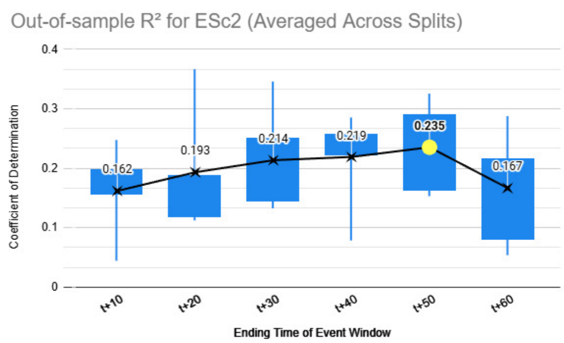
Figure 9: Systematic Estimation of Optimal Window Sizes for 30-Year Treasury Futures
Notes: The horizontal axis of each figure depicts the end time of the considered event window lengths and the vertical axis represents the percentage points of price changes by the market directly and only due to the FOMC statement text. The cross points represent $\overline{R^2_{OOS}}$ for each event window size, where the solid yellow point represents the event window with the largest $\overline{R^2_{OOS}}$. For each event window, box-and-whisker plots are shown surrounding the corresponding averages. $0 \leq \overline{R^2_{OOS}} \leq 1$ represents the proportion of the mean squared error from predicting with the in-sample average explained by the superior out-of-sample performance of XLNet.



(a) SPX

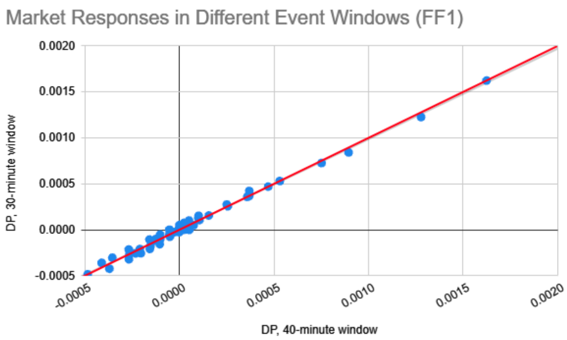


(b) $ESc1$

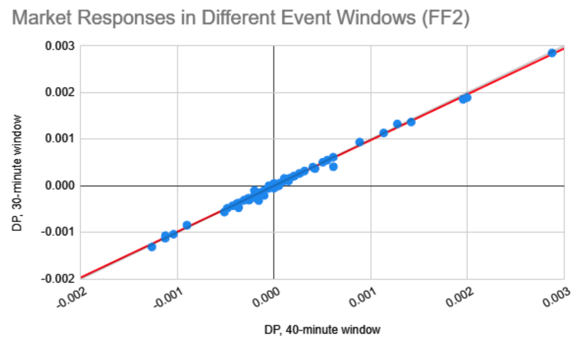


(c) $ESc2$

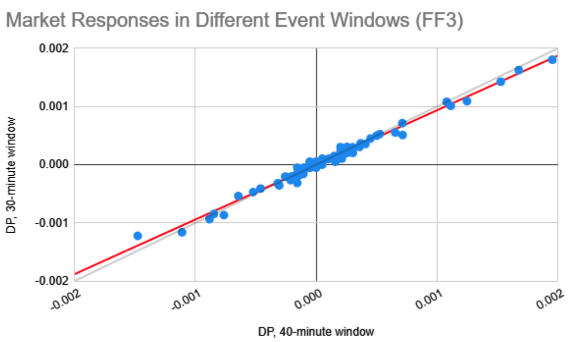
Figure 10: Systematic Estimation of Optimal Window Sizes for S&P 500 and E-mini Futures
Notes: The horizontal axis of each figure depicts the end time of the considered event window lengths and the vertical axis represents the percentage points of price changes by the market directly and only due to the FOMC statement text. The cross points represent $\overline{R^2_{OOS}}$ for each event window size, where the solid yellow point represents the event window with the largest $\overline{R^2_{OOS}}$. For each event window, box-and-whisker plots are shown surrounding the corresponding averages. $0 \leq \overline{R^2_{OOS}} \leq 1$ represents the proportion of the mean squared error from predicting with the in-sample average explained by the superior out-of-sample performance of XLNet.



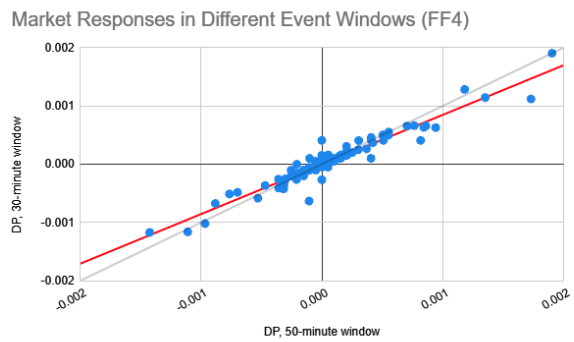
(a) $FF1^{**}$



(b) $FF2^{***}$

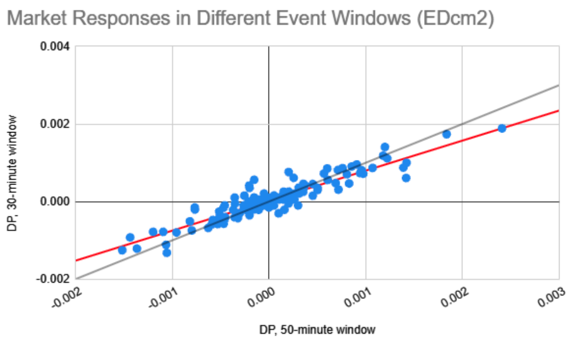


(c) $FF3^{***}$

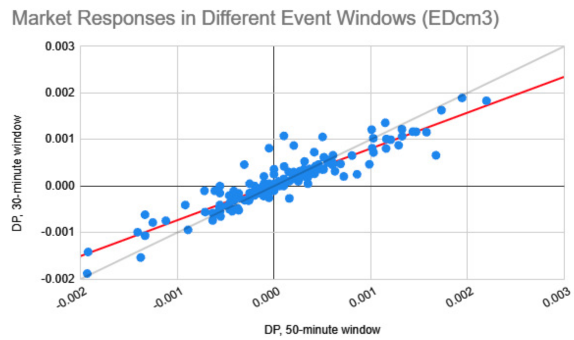


(d) $FF4^{***}$

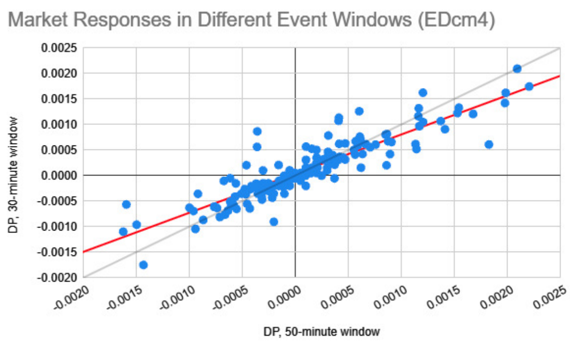
Figure 11: Comparing Market Responses in Different Event Windows for Federal Funds Futures
Notes: The horizontal axis depicts the price log-difference within the systematically estimated event window length. The vertical axis represents DP_{t+20}. The 45-degree line is depicted as grey. The blue dots are market reactions on scheduled FOMC meetings. The price-log differences calculated within the optimal window lengths are regressed on DP_{t+20} through OLS. If the slope coefficient is greater (less) than one and its difference with one is statistically significant for at most $\alpha = 0.10$, then the financial market under-reacts to the information content of FOMC statements on release, ex post, and is depicted in red. ** sig. at the 5% level, *** sig. at the 1% level.



(a) $EDcm2^{***}$

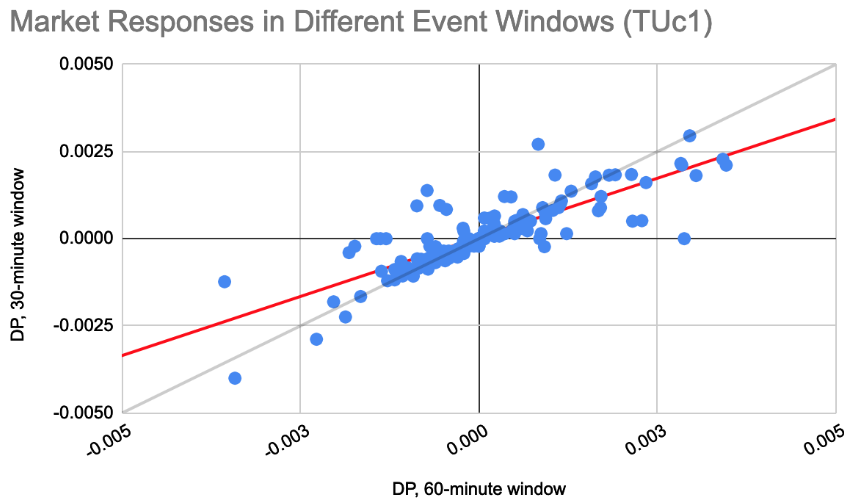


(b) $EDcm3^{***}$

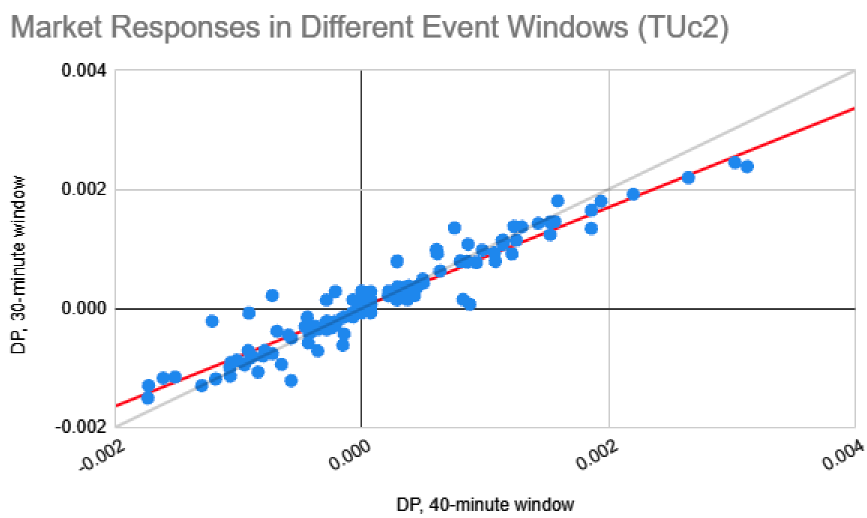


(c) $EDcm4^{***}$

Figure 12: Comparing Market Responses in Different Event Windows for Eurodollar Futures
Notes: The horizontal axis depicts the price log-difference within the systematically estimated event window length. The vertical axis represents DP_{t+20}. The 45-degree line is depicted as grey. The blue dots are market reactions on scheduled FOMC meetings. The price-log differences calculated within the optimal window lengths are regressed on DP_{t+20} through OLS. If the slope coefficient is greater (less) than one and its difference with one is statistically significant for at most $\alpha = 0.10$, then the financial market under-reacts to the information content of FOMC statements on release, ex post, and is depicted in red. ** sig. at the 5% level, *** sig. at the 1% level.

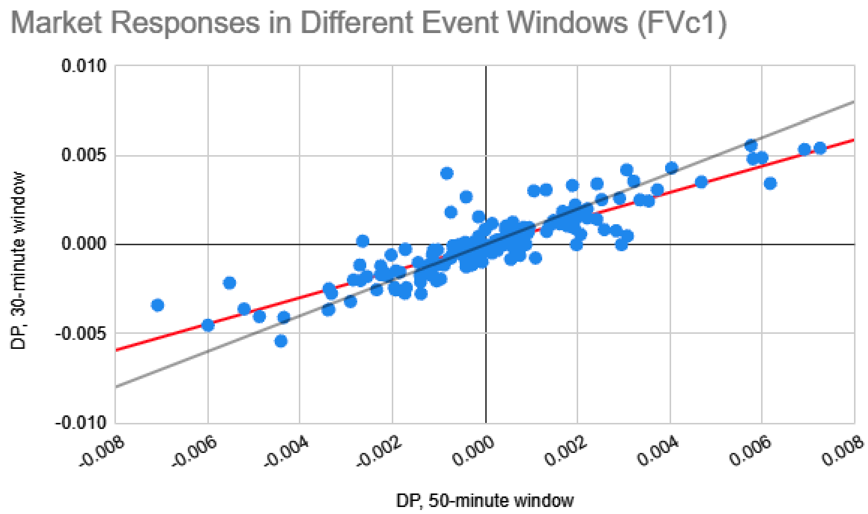


(a) $TUc1^{***}$

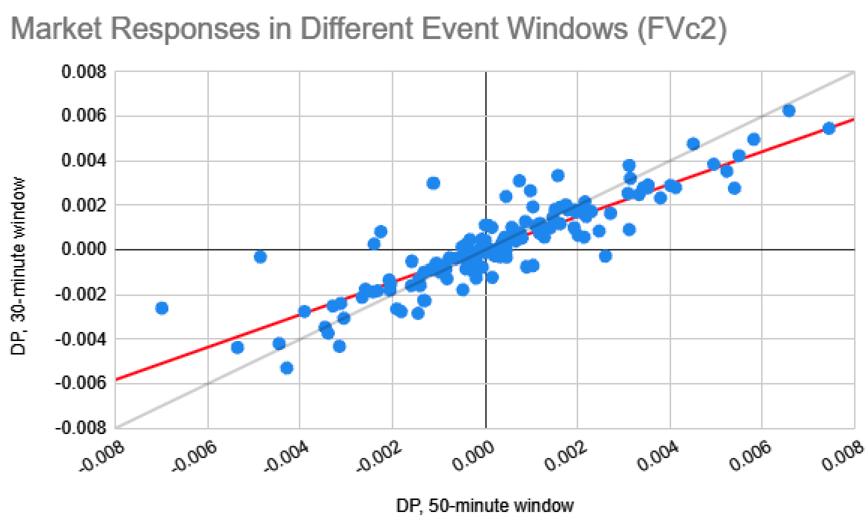


(b) $TUc2^{***}$

Figure 13: Comparing Market Responses in Different Event Windows for 2-Year Treasury Futures
Notes: The horizontal axis depicts the price log-difference within the systematically estimated event window length. The vertical axis represents DP_{t+20}. The 45-degree line is depicted as grey. The blue dots are market reactions on scheduled FOMC meetings. The price-log differences calculated within the optimal window lengths are regressed on DP_{t+20} through OLS. If the slope coefficient is greater (less) than one and its difference with one is statistically significant for at most $\alpha = 0.10$, then the financial market under-reacts to the information content of FOMC statements on release, ex post, and is depicted in red. ** sig. at the 5% level, *** sig. at the 1% level.



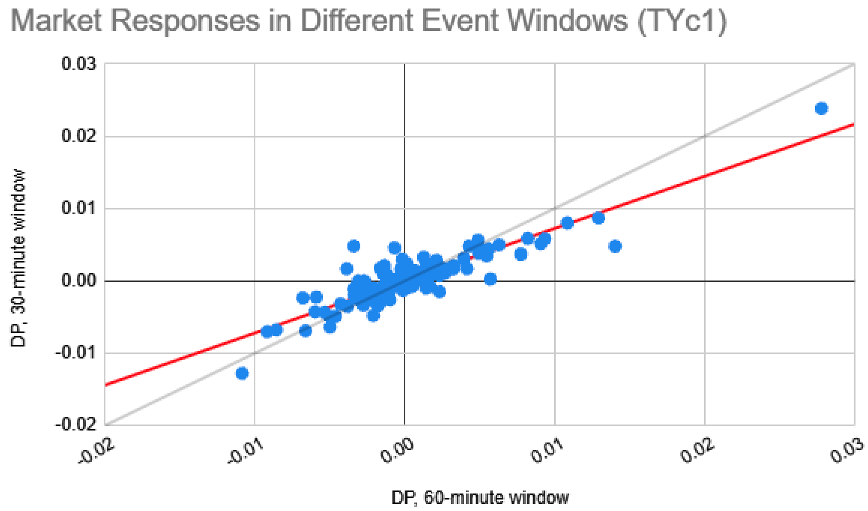
(a) $FVc1^{***}$



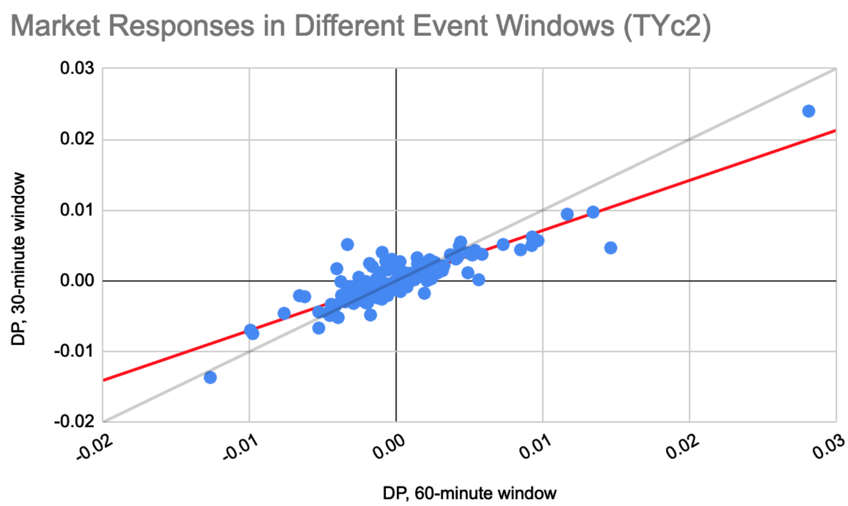
(b) $FVc2^{***}$

Figure 14: Comparing Market Responses in Different Event Windows for 5-Year Treasury Futures

Notes: The horizontal axis depicts the price log-difference within the systematically estimated event window length. The vertical axis represents DP_{t+20}. The 45-degree line is depicted as grey. The blue dots are market reactions on scheduled FOMC meetings. The price-log differences calculated within the optimal window lengths are regressed on DP_{t+20} through OLS. If the slope coefficient is greater (less) than one and its difference with one is statistically significant for at most $\alpha = 0.10$, then the financial market under-reacts to the information content of FOMC statements on release, ex post, and is depicted in red. ** sig. at the 5% level, *** sig. at the 1% level.



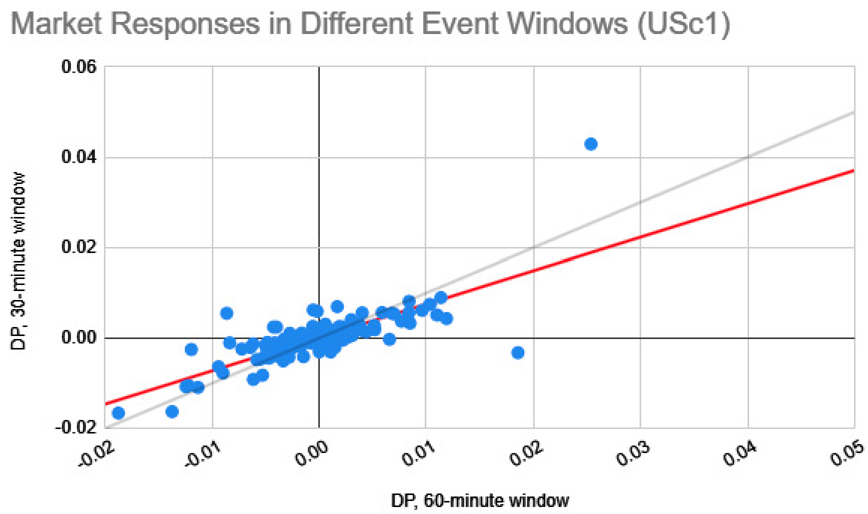
(a) $TYc1^{***}$



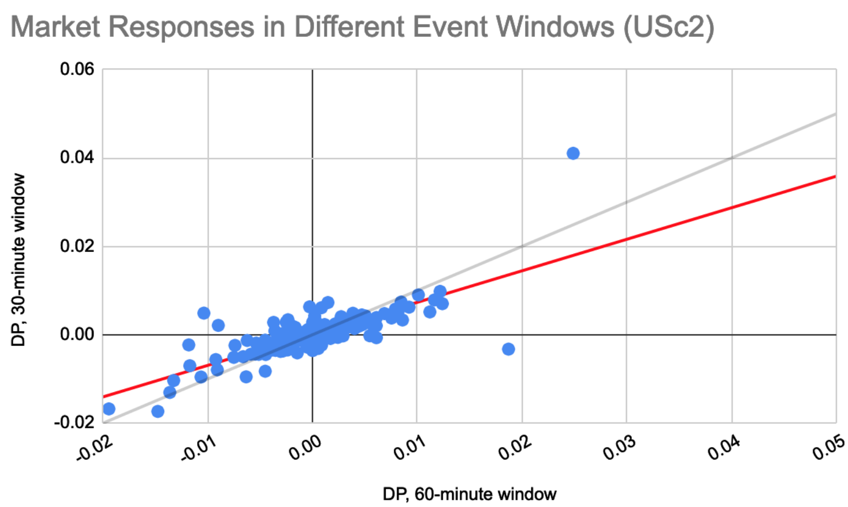
(b) $TYc2^{***}$

Figure 15: Comparing Market Responses in Different Event Windows for 10-Year Treasury Futures

Notes: The horizontal axis depicts the price log-difference within the systematically estimated event window length. The vertical axis represents DP_{t+20}. The 45-degree line is depicted as grey. The blue dots are market reactions on scheduled FOMC meetings. The price-log differences calculated within the optimal window lengths are regressed on DP_{t+20} through OLS. If the slope coefficient is greater (less) than one and its difference with one is statistically significant for at most $\alpha = 0.10$, then the financial market under-reacts to the information content of FOMC statements on release, ex post, and is depicted in red. ** sig. at the 5% level, *** sig. at the 1% level.

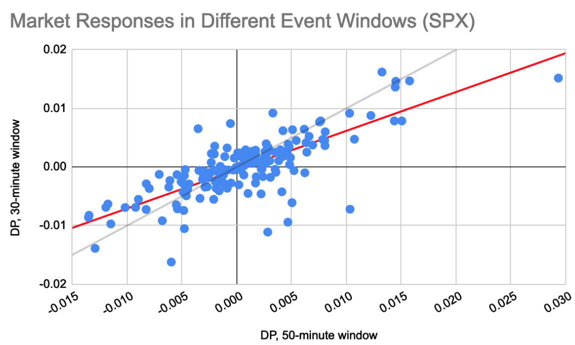


(a) $USc1^{***}$

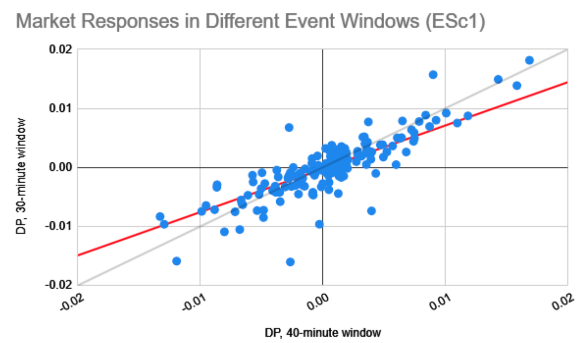


(b) $USc2^{***}$

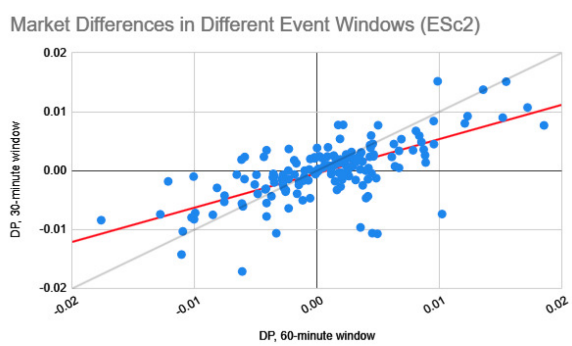
Figure 16: Comparing Market Responses in Different Event Windows for 30-Year Treasury Futures
Notes: The horizontal axis depicts the price log-difference within the systematically estimated event window length. The vertical axis represents DP_{t+20}. The 45-degree line is depicted as grey. The blue dots are market reactions on scheduled FOMC meetings. The price-log differences calculated within the optimal window lengths are regressed on DP_{t+20} through OLS. If the slope coefficient is greater (less) than one and its difference with one is statistically significant for at most $\alpha = 0.10$, then the financial market under-reacts to the information content of FOMC statements on release, ex post, and is depicted in red. ** sig. at the 5% level, *** sig. at the 1% level.



(a) SPX^{***}

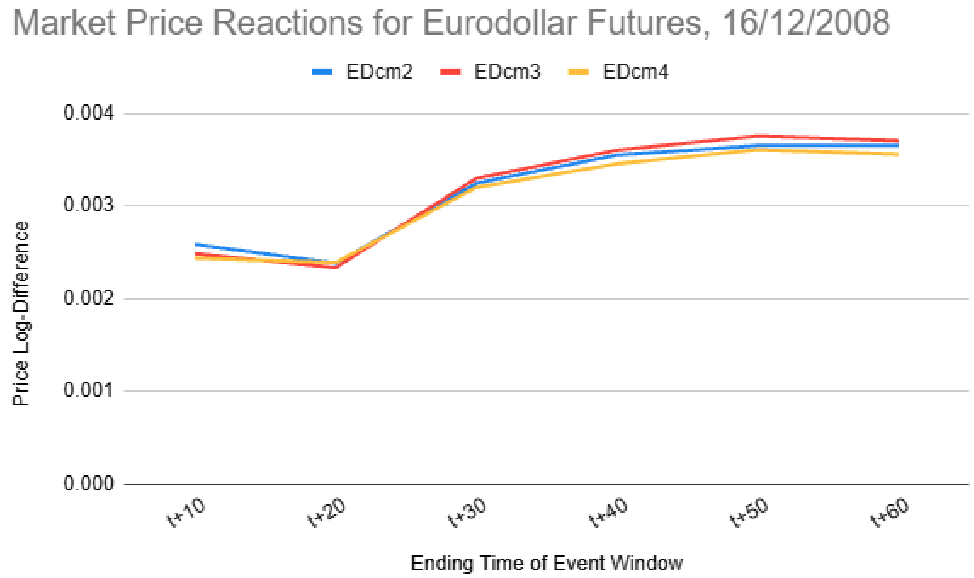


(b) $ESc1^{***}$

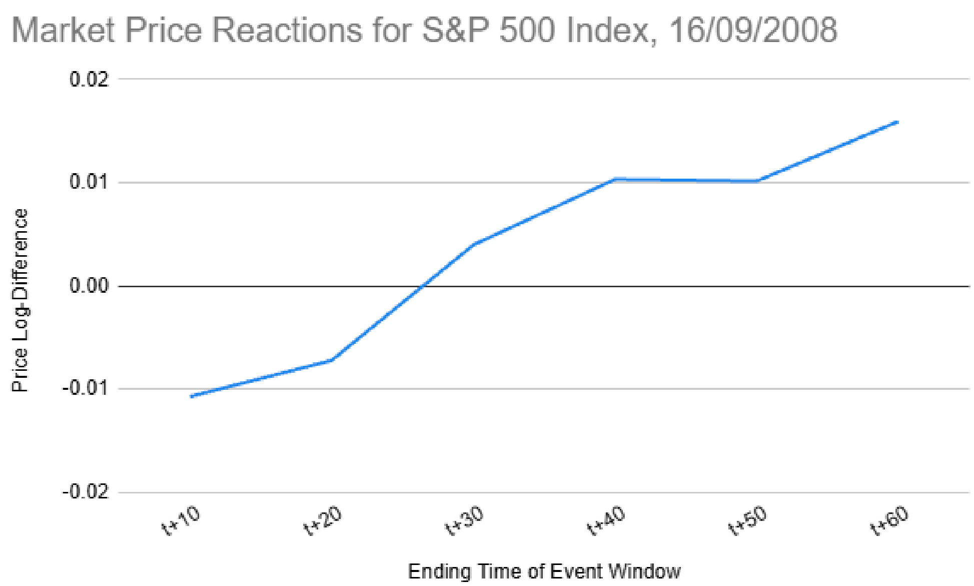


(c) $ESc2^{***}$

Figure 17: Comparing Market Responses in Different Event Windows for S&P 500 and E-mini Futures
Notes: The horizontal axis depicts the price log-difference within the systematically estimated event window length. The vertical axis represents DP_{t+20}. The 45-degree line is depicted as grey. The blue dots are market reactions on scheduled FOMC meetings. The price-log differences calculated within the optimal window lengths are regressed on DP_{t+20} through OLS. If the slope coefficient is greater (less) than one and its difference with one is statistically significant for at most $\alpha = 0.10$, then the financial market under-reacts to the information content of FOMC statements on release, ex post, and is depicted in red. ** sig. at the 5% level, *** sig. at the 1% level.



(a) Eurodollar Futures



(b) SPX

Figure 18: Responses of Eurodollar Futures and S&P 500 Markets to FOMC Statements
Notes: The top (bottom) sub-figure depicts the price log-differences of Eurodollar futures markets (the S&P 500 Index market) for different event window lengths after the release of the 16 December (September), 2008 FOMC statement. The horizontal axis of each figure depicts the end time of the considered event window lengths and the vertical axis represents the price-log differences.

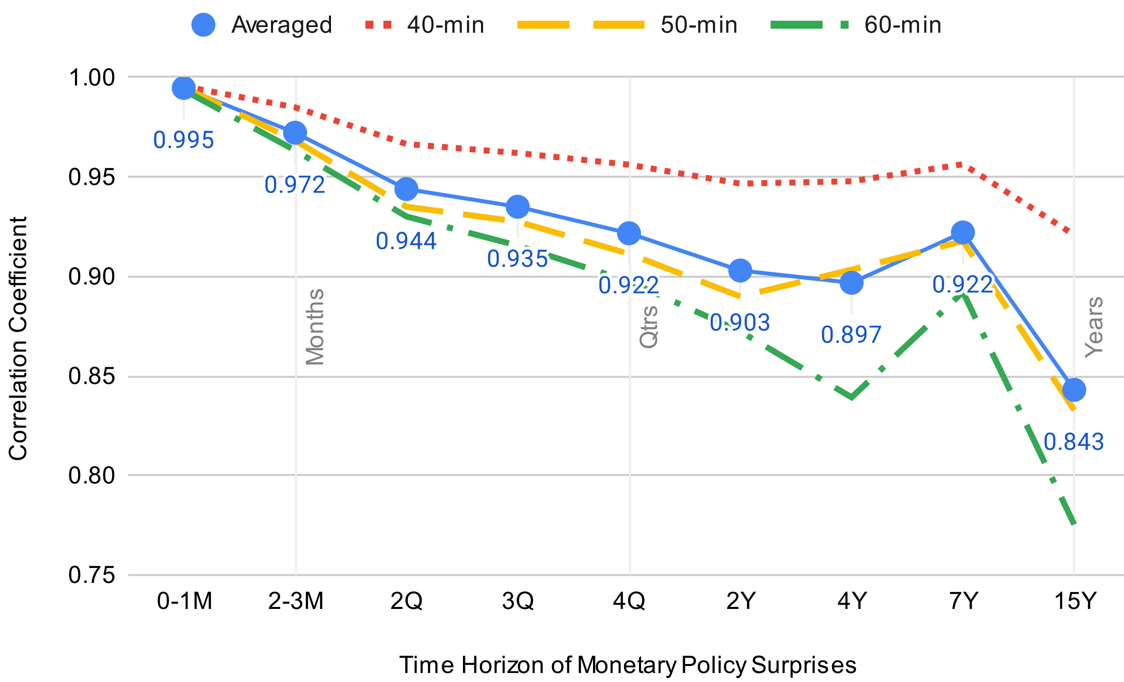
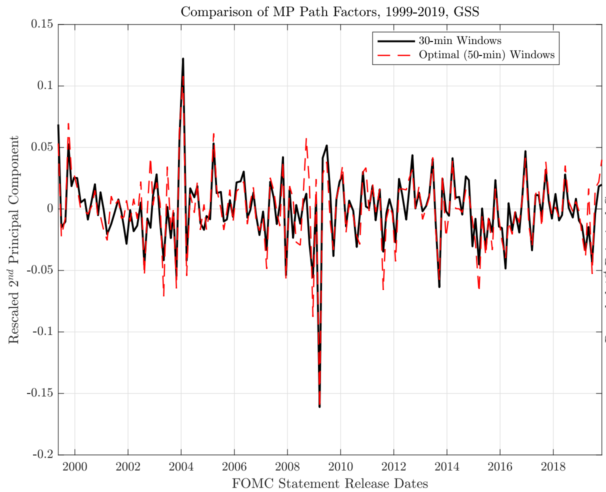
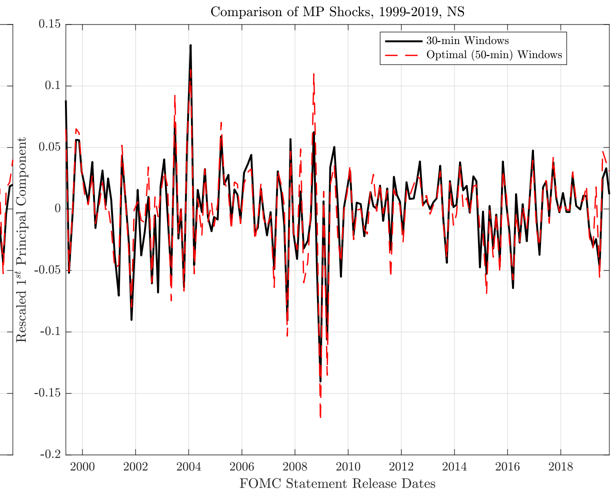


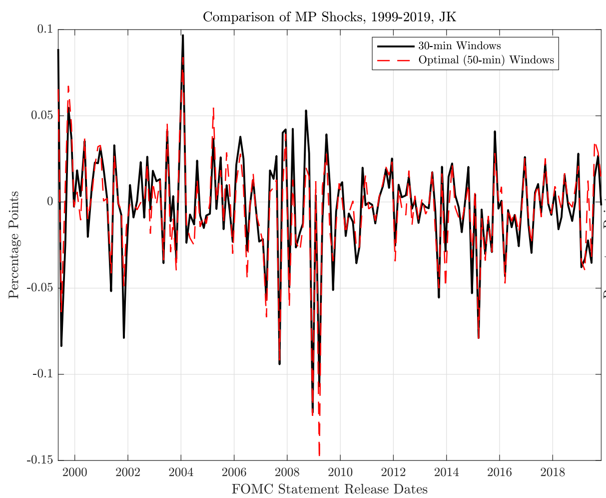
Figure 19: Correlation Between Monetary Policy Surprises Calculated in Optimal v. 30-minute Window Lengths
Notes: The horizontal axis depicts the time horizons of interest rate surprises. The vertical axis represents the Pearson correlation coefficient between the surprises calculated within optimal event window lengths v. 30 minutes. The red-dotted, yellow-dashed, and green-mixed lines represent the correlations calculated for surprises measured within the optimally-found 40, 50, and 60 minutes, respectively. The blue-solid line represents the correlations averaged across the three optimal window lengths. "0–1M" is interest rate surprise calculated using information from front-month and 1-month-ahead Federal Funds futures. "2–3M" represent expectations calculated from 2-month and 3-month-ahead Federal Funds futures. The time horizons for the Treasury futures contracts and resulting surprises are approximated by Gürkaynak, Kisacikoğlu, et al. (2020).



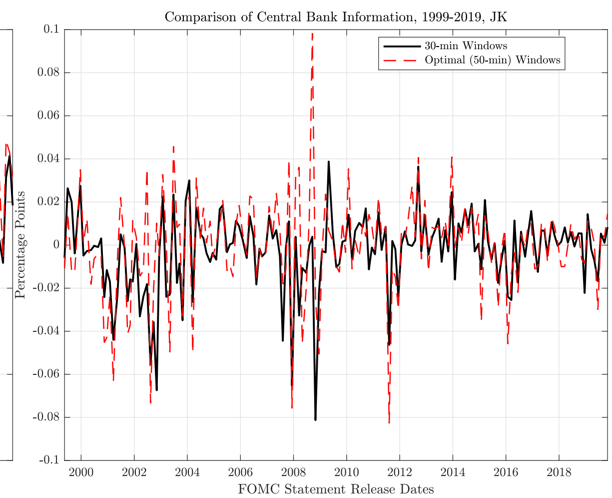
(a) GSS_P



(b) NS_{MP}



(c) JK_{MP}



(d) JK_{CBI}

Figure 20: Comparing Monetary Policy Shock Series Derived from Optimal Window Length v. 30 Minutes

Notes: The horizontal axis represents FOMC statement release dates. The vertical axis are percentage points after rescaling each shock to be one-for-one with the daily change in the zero coupon, nominal one-year Treasury yield. For all construction methods, the black-solid and red-dotted lines represent the shocks derived from surprises measured within 30 minutes and the median optimal event window length of 50 minutes, respectively.

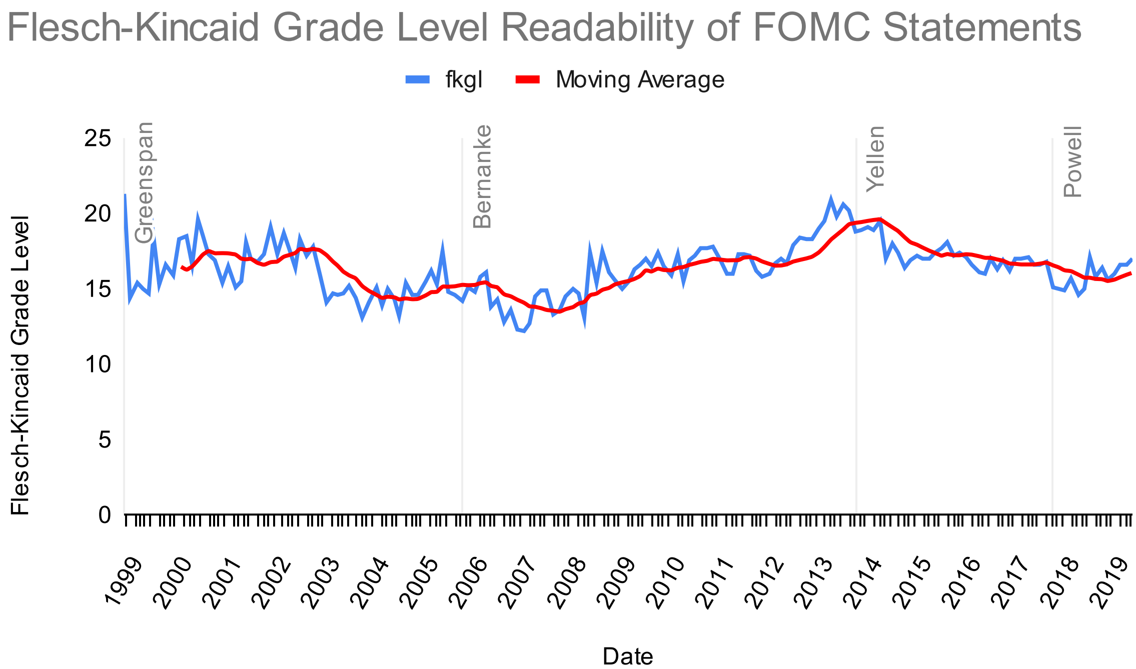


Figure 21: Flesch-Kincaid Grade Level Readability of FOMC Statements

Notes: The complexity of FOMC statements is measured by the Flesch-Kincaid Grade Level, defined as: $0.39 \times$ average sentence length $+ 11.8 \times$ average number of syllables per word $-$ 15.59. From left to right, the vertical grey lines indicate the first FOMC meeting with Greenspan, Bernanke, Yellen, and Powell as Fed Chair. The moving average is calculated with a period of 10.

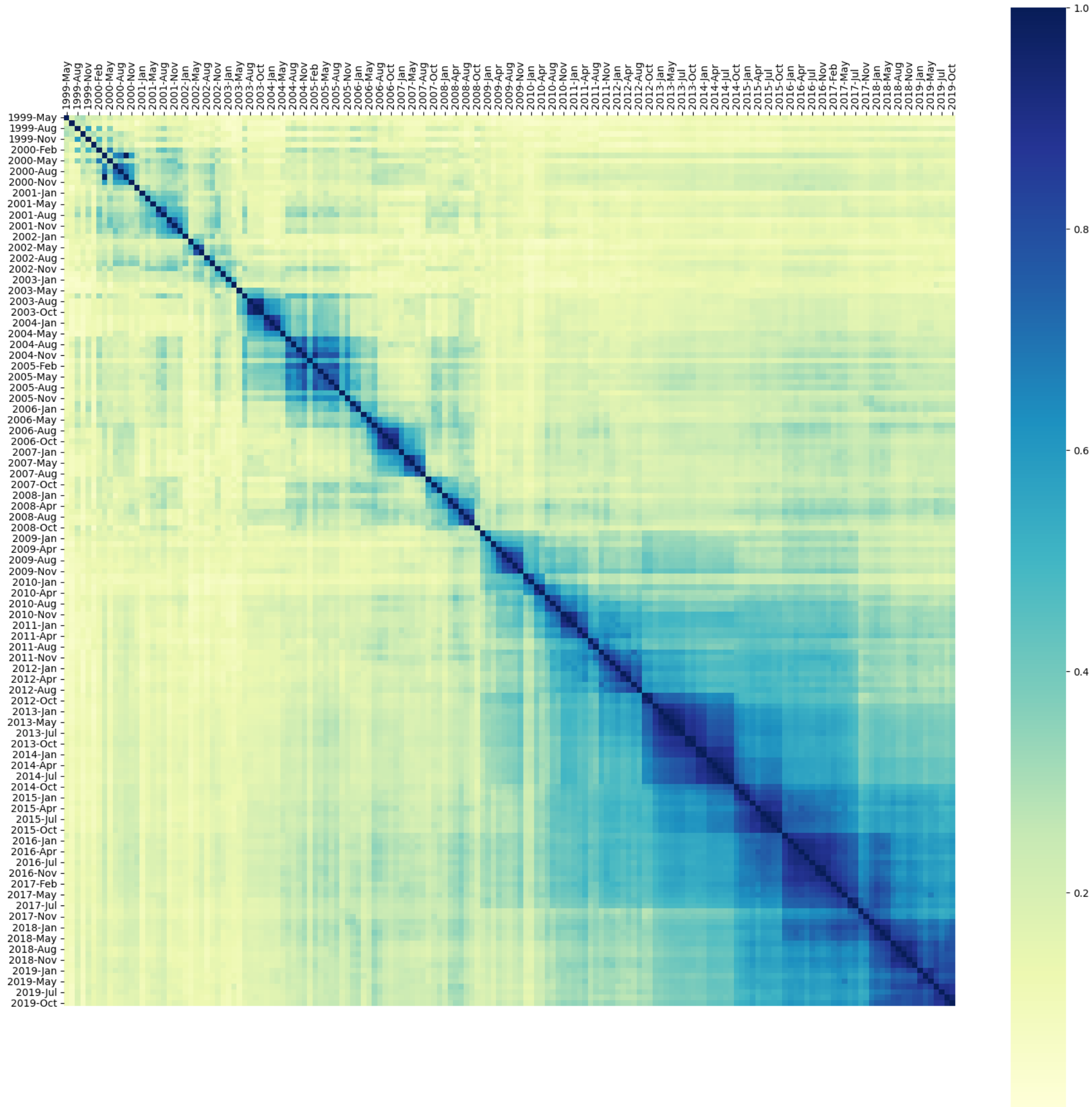


Figure 22: Document Similarity Matrix for FOMC Statements

Notes: Each element is the cosine similarity between two FOMC statements of that row and column. The cosine similarity value measures how similar the terms of both statements are. The darker shade of blue represents pairs of documents that have higher similarity measures closer to one, whilst the light shade of green represents pairs of documents that do not have terms in common and similarity values closer to zero. The main diagonal has all ones because the cosine similarity value is calculated between an FOMC statement with itself. All FOMC statements have been preprocessed such that all words are lowercase, all words are reduced to base form, and all stop-words are removed.

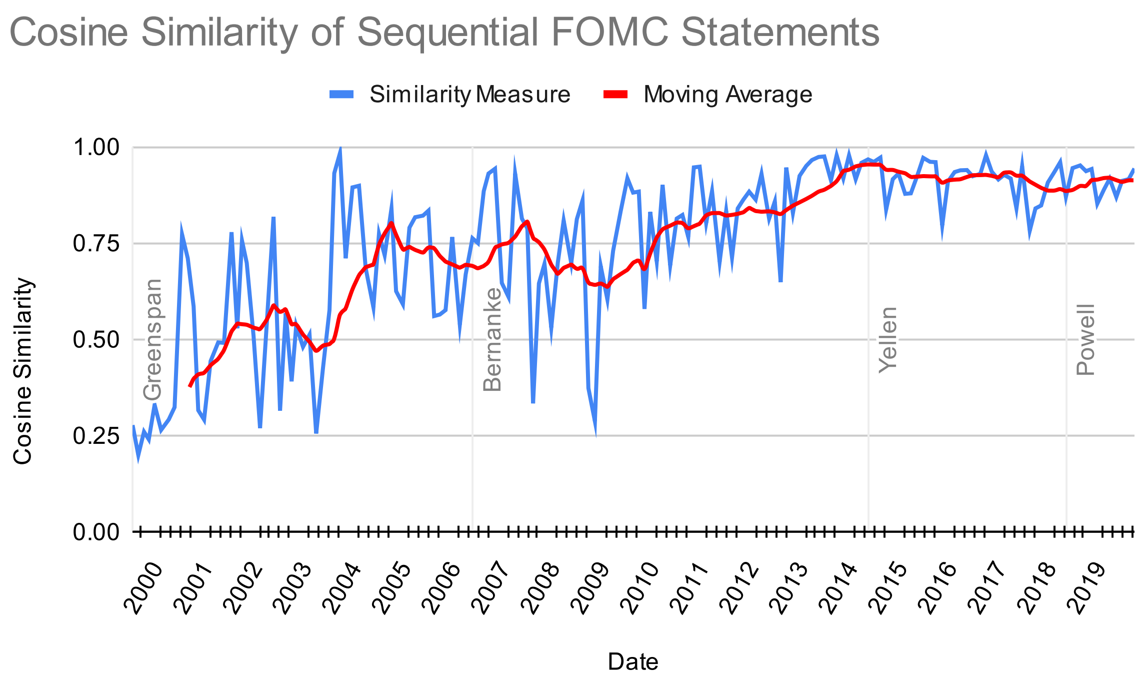


Figure 23: S^1 Cosine Similarity of Sequential FOMC Statements

Notes: S^1 is the cosine similarity between the TFIDF value of an FOMC statement and that of the immediately previous FOMC statement. Cosine similarity values closer to one (zero) mean the statements share more (less) common term usage. The moving average is calculated with a period of 10.

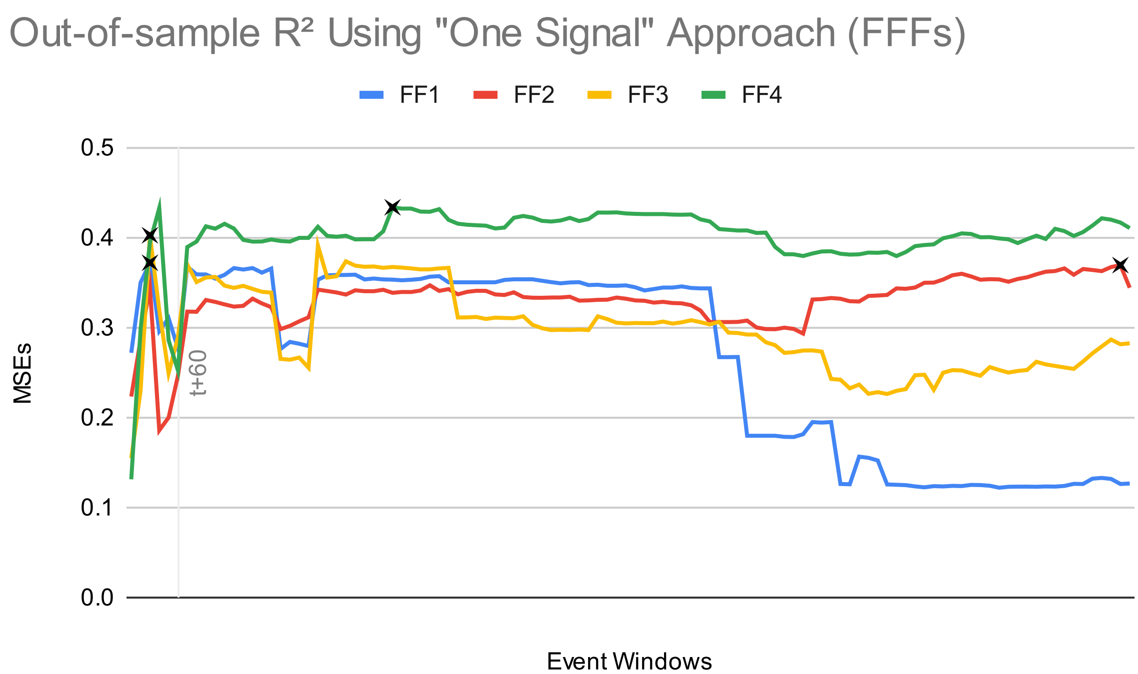


Figure 24: $\overline{R^2_{OOS}}$ Calculated Using the "One Signal" Approach for Federal Funds Futures

Notes: The horizontal axis depicts the event window lengths, starting from a 20-minute event window and ending at an event window starting 10 minutes before and ending 18 hours after FOMC statement release. The cross points represent the event window length associated with the largest $\overline{R^2_{OOS}}$. Estimates to the left of the vertical grey line labelled "$t + 60$" are calculated using the "joint' approach. The 1-month and 3-month-ahead federal funds futures contract are the two exceptions that sees the largest $\overline{R^2_{OOS}}$ within a window length than the systematically estimated length. As a robustness check, $\overline{R^2_{OOS}}$ was calculated with systematic estimation for both futures and considered event window lengths, which can be found in the rightmost box-and-whisker plot of Sub-figures 4b and 4d, respectively.

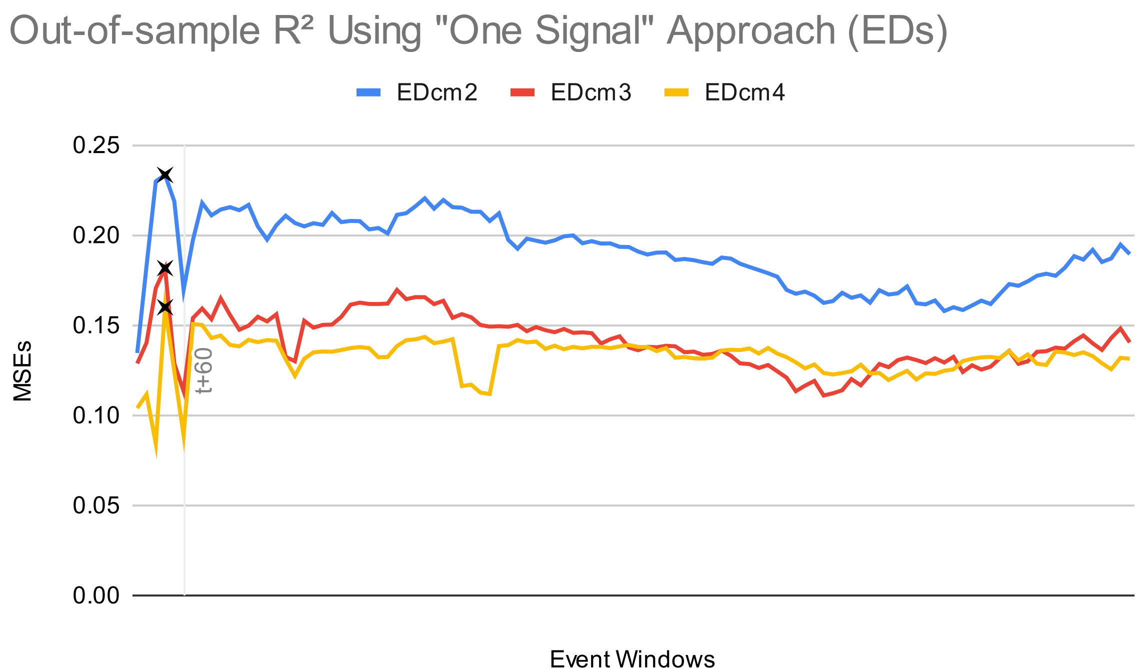


Figure 25: $\overline{R^2_{OOS}}$ Calculated Using the "One Signal" Approach for Eurodollar Futures

Notes: The horizontal axis depicts the event window lengths, starting from a 20-minute event window and ending at an event window starting 10 minutes before and ending 18 hours after FOMC statement release. The cross points represent the event window length associated with the largest $\overline{R^2_{OOS}}$. Estimates to the left of the vertical grey line labelled "$t + 60$" are calculated using the "joint" approach.

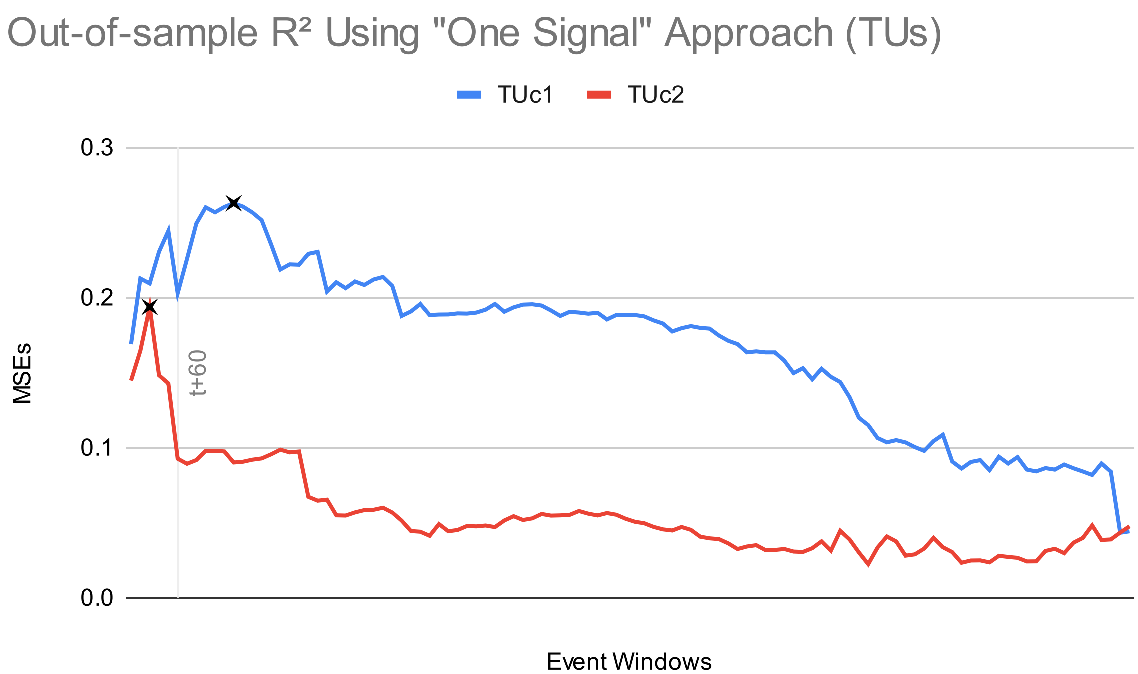


Figure 26: $\overline{R^2_{OOS}}$ Calculated Using the "One Signal" Approach for 2-year Treasury Futures

Notes: The horizontal axis depicts the event window lengths, starting from the systematically estimated event window length and ending at an event window starting 10 minutes before and ending 18 hours after FOMC statement release. The cross points represent the event window length associated with the largest $\overline{R^2_{OOS}}$. Estimates to the left of the vertical grey line labelled "$t + 60$" are calculated using the "joint" approach. The front-month 2-year Treasury futures contract is the one exception that sees the largest $\overline{R^2_{OOS}}$ within a window length than the systematically estimated length. As a robustness check, $\overline{R^2_{OOS}}$ was calculated with systematic estimation for the futures contract and considered event window length, which can be found in the rightmost box-and-whisker plot of Sub-figure 6a.

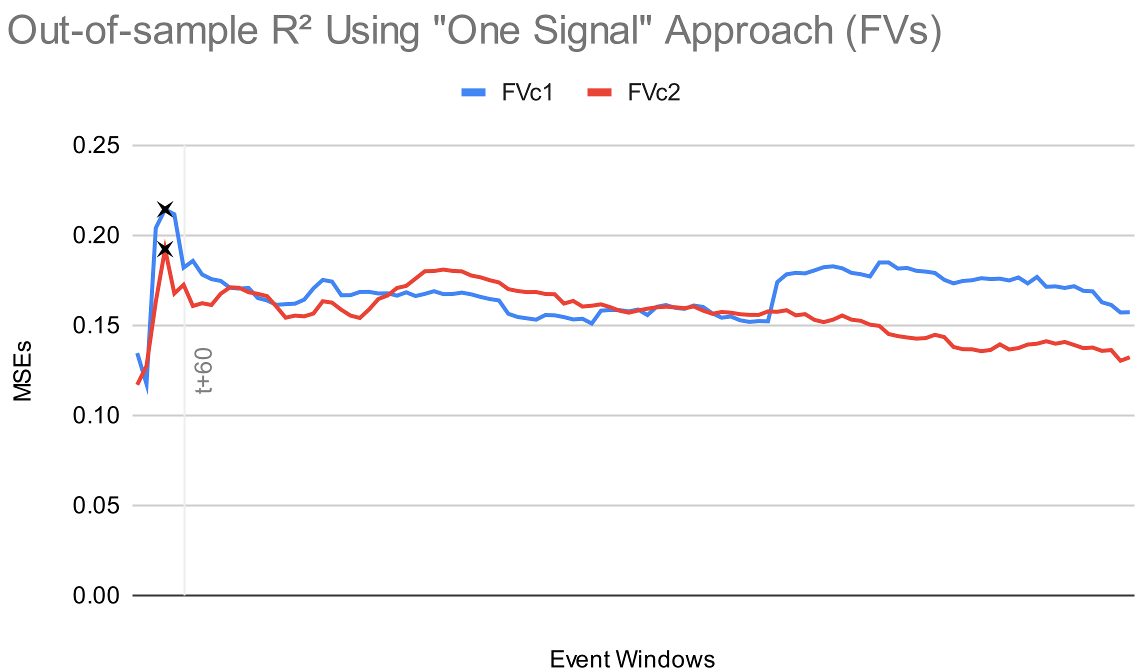


Figure 27: $\overline{R^2_{OOS}}$ Calculated Using the "One Signal" Approach for 5-year Treasury Futures

Notes: The horizontal axis depicts the event window lengths, starting from the systematically estimated event window length and ending at an event window starting 10 minutes before and ending 18 hours after FOMC statement release. The cross points represent the event window length associated with the largest $\overline{R^2_{OOS}}$. Estimates to the left of the vertical grey line labelled "$t + 60$" are calculated using the "joint" approach.

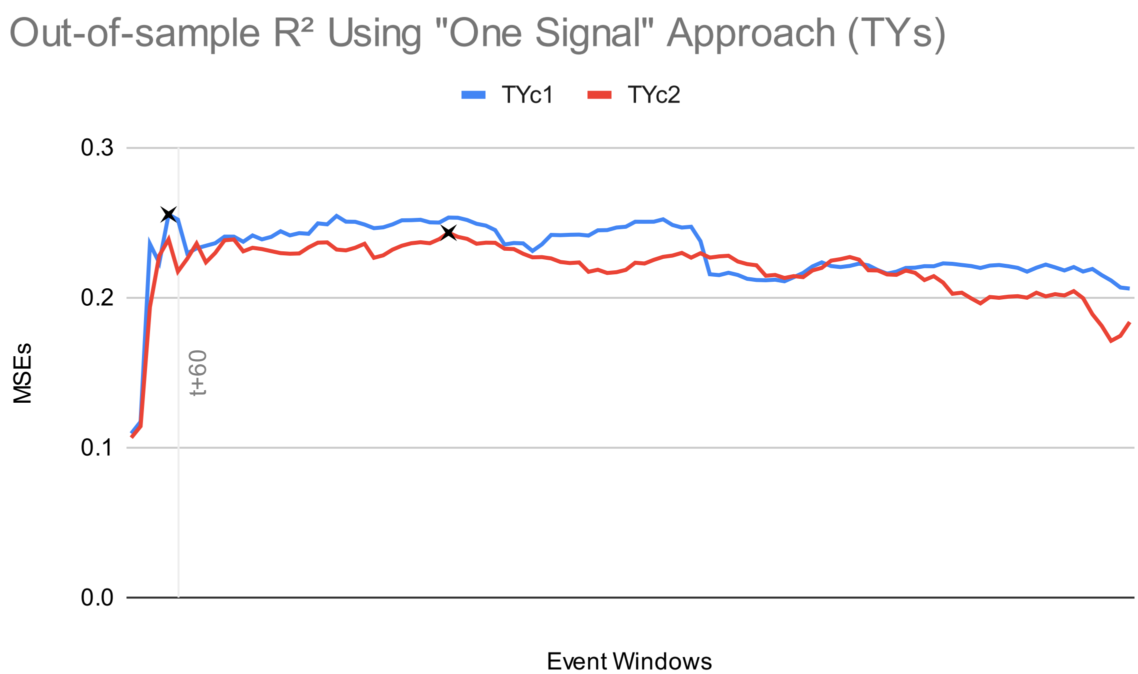


Figure 28: $\overline{R^2_{OOS}}$ Calculated Using the "One Signal" Approach for 10-year Treasury Futures

Notes: The horizontal axis depicts the event window lengths, starting from the systematically estimated event window length and ending at an event window starting 10 minutes before and ending 18 hours after FOMC statement release. The cross points represent the event window length associated with the largest $\overline{R^2_{OOS}}$. Estimates to the left of the vertical grey line labelled "$t + 60$" are calculated using the "joint" approach. The second-month 10-year Treasury futures contract is the one exception that sees the largest $\overline{R^2_{OOS}}$ within a window length than the systematically estimated length. As a robustness check, $\overline{R^2_{OOS}}$ was calculated with systematic estimation for the futures contract and considered event window length, which can be found in the rightmost box-and-whisker plot of Sub-figure 8b.

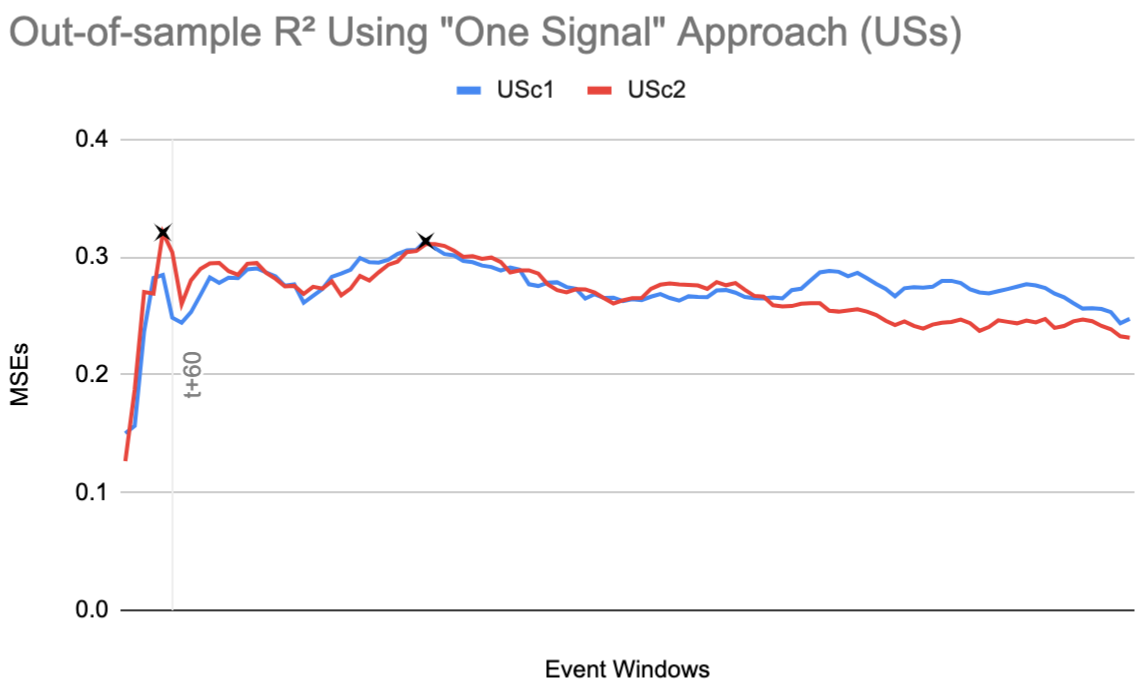


Figure 29: $\overline{R^2_{OOS}}$ Calculated Using the "One Signal" Approach for 30-year Treasury Futures

Notes: The horizontal axis depicts the event window lengths, starting from the systematically estimated event window length and ending at an event window starting 10 minutes before and ending 18 hours after FOMC statement release. The cross points represent the event window length associated with the largest $\overline{R^2_{OOS}}$. Estimates to the left of the vertical grey line labelled "$t + 60$" are calculated using the "joint" approach. The front-month 30-year Treasury futures contract is the one exception that sees the largest $\overline{R^2_{OOS}}$ within a window length than the systematically estimated length. As a robustness check, $\overline{R^2_{OOS}}$ was calculated with systematic estimation for the futures contract and considered event window length, which can be found in the rightmost box-and-whisker plot of Sub-figure 9a.

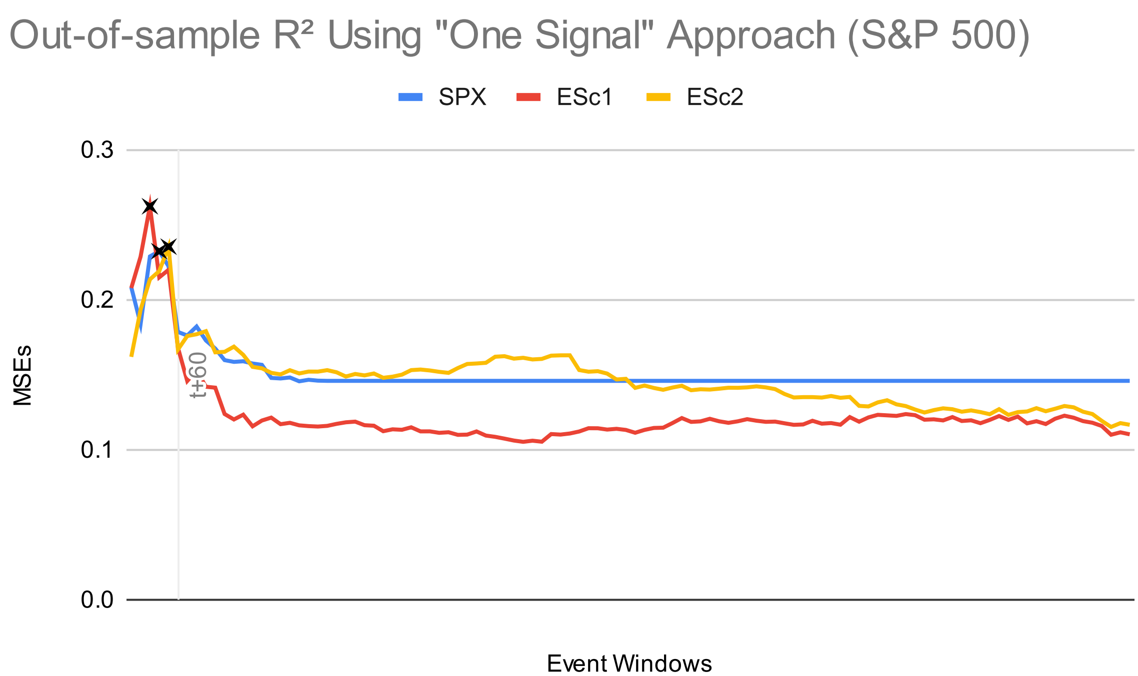


Figure 30: $\overline{R^2_{OOS}}$ Calculated Using the "One Signal" Approach for S&P 500 and E-mini Futures

Notes: The horizontal axis depicts the event window lengths, starting from the systematically estimated event window length and ending at an event window starting 10 minutes before and ending 18 hours after FOMC statement release. The cross points represent the event window length associated with the largest $\overline{R^2_{OOS}}$. Estimates to the left of the vertical grey line labelled "$t + 60$" are calculated using the "joint" approach.

Tables

	Scenario 1	Scenario 2	Scenario 3
Framework 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 1: Framework Simulation Parameters and Results for Different Asset Market Scenarios
Notes: The results are from 10,000 simulations of the asset price framework for the three asset market scenarios considered. t^* and $\hat{t}$ are defined as the time at which the asset market fundamentally reacts to FOMC announcements on average, where the former is calculated using the fundamental price component and the latter with the observed signal according to the price framework.

Name	Maturity	Ticker	Sample	Observations
Inputs				
FOMC Statements	N/A	N/A	1999–2019	165
Outputs				
Federal Funds Rate Futures	Front-month	$FFc1$	1999–2019	165
Federal Funds Rate Futures	1-month-ahead	$FFc2$	1999–2019	165
Federal Funds Rate Futures	2-month-ahead	$FFc3$	1999–2019	165
Federal Funds Rate Futures	3-month-ahead	$FFc4$	1999–2019	165
Eurodollar Futures	2-quarter	$EDcm2$	1999–2019	165
Eurodollar Futures	3-quarter	$EDcm3$	1999–2019	165
Eurodollar Futures	4-quarter	$EDcm4$	1999–2019	165
2-year Treasury Futures	Front-month	$TUc1$	1999–2019	165
2-year Treasury Futures	Second-month	$TUc2$	1999–2019	165
5-year Treasury Futures	Front-month	$FVc1$	1999–2019	165
5-year Treasury Futures	Second-month	$FVc2$	1999–2019	165
10-year Treasury Futures	Front-month	$TYc1$	1999–2019	165
10-year Treasury Futures	Second-month	$TYc2$	1999–2019	165
30-year Treasury Futures	Front-month	$USc1$	1999–2019	165
30-year Treasury Futures	Second-month	$USc2$	1999–2019	165
S&P 500 Index	N/A	SPX	1999–2019	165
S&P 500 E-mini Futures	Front-month	$ESc1$	1999–2019	165
S&P 500 E-mini Futures	Second-month	$ESc2$	1999–2019	165

Table 2: Independent and Dependent Variables for Systematic Estimation of Appropriate Event Window Lengths by Neural Networks

Notes: The table shows the FOMC statements and financial market asset prices considered as independent and dependent variables, respectively, in my analysis. The statements are collected from the Board of Governors of the Federal Reserve System website and the asset prices are from the Thomson Reuters Tick History database. All series begin in May 1999 and end in October 2019. *Ticker* refers to the Reuters Instrument Code (RIC).

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
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 3: XLNet Hyperparameters for Fine-tuning

Notes: * 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 initial values.

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.**
$FVc1$	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%	26.2%	+**3.3 p.p.**
$ESc2$	19.3%	23.5%	+**4.2 p.p.**

Table 4: Differences of $\overline{R^2_{OOS}}$ between 30-minute and Optimal Event Windows

Series Name	Notation	Description
Gürkaynak, Sack, and Swanson (2005) Target Shocks	GSS_T	First principal component of monetary policy surprises that is rotated such that it drives unexpected changes in the surprise in the current federal funds rate
Gürkaynak, Sack, and Swanson (2005) Path Shocks	GSS_P	Second principal component of monetary policy surprises that is rotated such that on average, it has no effect on the surprise in the current federal funds rate
Nakamura and Steinsson (2018) Shocks	NS_{MP}	First principal component of monetary policy surprises
Jarociński and Karadi (2020) Shocks	JK_{MP}	First principal component of monetary policy surprises that have negative co-movement with stock market changes
Jarociński and Karadi (2020) Central Bank Information	JK_{CBI}	First principal component of monetary policy surprises that have positive co-movement with stock market changes

Table 5: Monetary Policy Shock Series

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 6: Descriptive Statistics for Monetary Policy Shock Series

Notes: Numbers in parentheses are summary statistics for each shock series derived from monetary policy surprises calculated within the median optimal event window length of 50 minutes.

	Both	30-minute Window			Optimal Window			**Difference**		
	ΔTY_1	ΔTY_2	ΔTY_5	ΔTY_{10}	ΔTY_2	ΔTY_5	ΔTY_{10}	ΔTY_2	ΔTY_5	ΔTY_{10}
GSS_T	1.00***	0.82***	0.15	-0.37	0.78***	0.08	-0.42	**-0.04**	**-0.07**	**-0.05**
	(0.29)	(0.38)	(0.51)	(0.53)	(0.31)	(0.41)	(0.42)			
GSS_P	1.00***	1.46***	1.89***	1.64***	1.51***	1.92***	1.66***	**+0.05**	**+0.04**	**+0.02**
	(0.11)	(0.12)	(0.26)	(0.35)	(0.09)	(0.20)	(0.29)			
NS_{MP}	1.00***	1.24***	1.29***	0.94***	1.30***	1.39***	1.06***	**+0.06**	**+0.11**	**+0.11**
	(0.09)	(0.12)	(0.21)	(0.25)	(0.13)	(0.21)	(0.25)			
JK_{MP}	1.00***	1.30***	1.39***	0.99***	1.35***	1.52***	1.16***	**+0.04**	**+0.13**	**+0.17**
	(0.14)	(0.18)	(0.28)	(0.33)	(0.16)	(0.30)	(0.39)			
JK_{CBI}	1.00***	1.04***	1.00***	0.82***	1.20***	1.14***	0.85***	**+0.16**	**+0.14**	**+0.03**
	(0.31)	(0.37)	(0.39)	(0.34)	(0.22)	(0.26)	(0.27)			

Table 7: Differences in Responses of Nominal Interest Rates to Shocks from Event Window Choice

Notes: Each estimate comes from a separate OLS regression. For each regression, the dependent variable is the one-day change in end-of-day Treasury yields, represented by columns. The independent variable is the change in monetary policy shock series over a given event window around the time of scheduled FOMC announcements. Starting from the left, columns 3–5 represent the OLS regressions performed on shock series constructed within 30-minute windows. Columns 6–8 are equivalent, but for shocks constructed within the median optimal window length of 50 minutes. The sample period consists of all scheduled FOMC statement release dates from May 1999 through October 2019, resulting in 165 observations. Robust standard errors are reported in parentheses. Columns 9–11 represent the differences between the coefficients of the regressions using the optimal windows v. those using 30-minute windows. *** sig. at the 1% level.

	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**
	(1.66)	(0.65)	(0.58)	(1.72)	(0.53)	(0.46)			
GSS_P	2.21***	1.96***	1.74***	2.20***	2.03***	1.75***	**-0.00**	**+0.06**	**+0.01**
	(0.49)	(0.40)	(0.40)	(0.36)	(0.32)	(0.33)			
NS_{MP}	1.17***	1.29***	1.08***	1.31***	1.47***	1.20***	**+0.14**	**+0.18**	**+0.13**
	(0.80)	(0.30)	(0.27)	(0.63)	(0.27)	(0.26)			
JK_{MP}	1.40***	1.40***	1.15***	1.66***	1.64***	1.38***	**+0.26**	**+0.24**	**+0.23**
	(0.92)	(0.39)	(0.35)	(0.66)	(0.42)	(0.41)			
JK_{CBI}	0.51	0.99***	0.85***	0.60	1.13***	0.84***	**+0.09**	**+0.14**	**-0.01**
	(0.87)	(0.37)	(0.29)	(0.85)	(0.33)	(0.26)			

Table 8: Differences in Responses of Real Interest Rates to Shocks from Event Window Choice

Notes: Each estimate comes from a separate OLS regression. For each regression, the dependent variable is the one-day change in end-of-day TIPS yields, represented by columns. The independent variable is the change in monetary policy shock series over a given event window around the time of scheduled FOMC announcements. Starting from the left, columns 3–5 represent the OLS regressions performed on shock series constructed within 30-minute windows. Columns 6–8 are equivalent, but for shocks constructed within the median optimal window length of 50 minutes. The sample period consists of all scheduled FOMC statement release dates from May 1999 through October 2019, resulting in 165 observations. Robust standard errors are reported in parentheses. Columns 9–11 represent the differences between the coefficients of the regressions using the optimal windows v. those using 30-minute windows. *** sig. at the 1% level.

	$DP_{SPX,t+20}$	$DP_{SPX,t+40}$	**Difference**
GSS_T	-8.40^{***}	-7.39^{***}	**+1.01**
	(2.78)	(2.95)	
GSS_P	-6.14^{***}	-6.85^{***}	**-0.71**
	(1.69)	(2.61)	
NS_{MP}	-6.92^{***}	-7.00^{***}	**-0.09**
	(1.27)	(1.84)	
JK_{MP}	-14.76^{***}	-17.46^{***}	**-2.69**
	(0.74)	(1.03)	
JK_{CBI}	15.19^{***}	14.08^{***}	**-1.12**
	(2.07)	(2.07)	

Table 9: Differences in Responses of Stock Prices to Shocks from Event Window Choice
Notes: Each estimate comes from a separate OLS regression. For each regression, the dependent variable is the price log-difference of the S&P 500 Index, represented by columns. The independent variable is the change in monetary policy shock series over a given event window around the time of scheduled FOMC announcements. Starting from the left, the second column represents the OLS regressions where both variables are measured within 30-minute windows. The third column has equivalent meaning, but using the median optimal event window length of 50 minutes. The sample period consists of all scheduled FOMC statement release dates from May 19999 through October 2019, resulting in 165 observations. Robust standard errors are reported in parentheses. The rightmost column represents the difference between the coefficients of the regressions using the optimal windows v. those using 30-minute windows. *** sig. at the 1% level.

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 10: Descriptive Statistics for Heterogeneity Analyses
Notes: The complexity of FOMC statements is measured by the Flesch-Kincaid Grade Level (FKGL), defined as: $0.39 \times \text{average sentence length} + 11.8 \times \text{average number of syllables per word} - 15.59$. S^1 is the cosine similarity measure between sequential FOMC statements.

Metric	Simple	**Complicated**	**Different**	Similar	Unity	**Dissents**
Minimised MSE						
Average	1.26e-5	**1.03e-5**	**1.14e-5**	1.14e-5	9.21e-6	**1.44e-5**
Event Window Length (Minutes)						
Average	59	**71**	**61**	51	61	**83**

Table 11: MSEs and Event Window Lengths Calculated Using the "One Signal" Approach, Conditioned by FOMC Statements Complexity, Similarity, and Presence of Dissents
Notes: The complexity of FOMC statements is measured by the Flesch-Kincaid Grade Level, defined as: $0.39 \times$ average sentence length $+ 11.8 \times$ average number of syllables per word $-$ 15.59, and displayed in the first two columns. Changes in FOMC statements are measured using a pairwise-statement cosine similarity measure and displayed in the third and fourth columns from the left. The event window lengths are displayed in minutes. "Simple" statements have grade levels up to 16.5. "Complicated" statements have grade levels above 16.5. "Different" are sequential statements with a cosine similarity of less than to 0.885. "Similar" are sequential statements with a cosine similarity of more than 0.885. "Unity" statements are those without votes of dissent. "Dissents" are statements with recorded dissent votes. For all futures contracts, event window lengths considered as outliers under the "one signal" approach are set equal to the median of the sub-set window lengths in order to lessen their effects.

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 12: FOMC Statement Base Terms with Top 30 TFIDF Scores
Notes: TFIDF is a weighted frequency combining word and document counts such that greater weight is given to words that are more informative about the information content of the FOMC statements relative to other statements where the words are not found. Specifically, the weighted term frequency gives higher weight to terms that occur more frequently in a given document. The term frequency is then divided by the number of documents that has this term appear. The more documents that have the word, the less importance and weight will be given to the word as it is less informative for distinguishing documents from one another.

A The Primary Accuracy Metric for Judging XLNet

As mentioned in Subsection 4.4, the primary metric considered by the neural network to judge its accuracy during fine-tuning for each sample split is the generalised R^2 defined in Hawinkel et al. (2024):

$$R^2_{OOS} = 1 - \frac{\widehat{MSE}}{\widehat{MST}} = 1 - \frac{T^{-1}\sum_{i=1}^{T}(y_i - \hat{y}_i)^2}{\frac{T+1}{T(T-1)}\sum_{i=1}^{T}(y_i - \overline{y_{IS}})^2}, \tag{A1}$$

where $\widehat{MSE}$ is the mean squared error of the neural network over the out-of-sample observations; $\widehat{MST}$ is the mean squared error calculated using the in-sample mean $\overline{y_{IS}}$ as prediction over all out-of-sample observations, and T is the size of the testing sample. Although the explicit objective function of the neural network during fine-tuning is to minimise $\widehat{MSE}$, this simultaneously maximises R^2_{OOS}. Other related metrics that are tracked by XLNet during its fine-tuning process are the out-of-sample Pearson correlation coefficient ρ between the predicted and actual observations, the out-of-sample mean absolute error, and the in-sample mean squared error. The last criterion is important for determining if the network is learning the relationship between the FOMC statement text and the price log-differences or not.

The interpretation of R^2_{OOS} can be better understood through a brief discussion about the underlying relationship that the neural network is approximating and using to predict, which is the nonparametric function mapping the text of FOMC statements to asset price changes. As is standard in the machine learning literature, the predictive quality of models is compared to the common baseline that states there is *no* relationship between the FOMC statement text and asset price changes and naively predicts with the in-sample average. When using the neural network to instead approximate this relationship and predict asset price changes for statements in the testing subsample, the R^2_{OOS} therefore states how much predictive error from naively using the in-sample average has been reduced. This interpretation implies that R^2_{OOS} does *not* follow the conventional definition of R^2, which is the proportion of variance in the data that is explained by a given model.[32] First, the conventional definition breaks down when applied to non-linear methods like neural networks because the variance of the observations is no longer comprised of only the model and residual variances. Second, applying the conventional R^2 metric onto out-of-sample observations breaks the spirit of prediction because it would be using the average outcome of the testing sample, which is supposed to be inaccessible to models during fitting.

B Construction of High-Frequency Monetary Surprises

B.1 Financial Data Overview

SoonTM.

[32]Note that the conventional definition is equivalent to the definition comparing a given model to the "naive model" when applied to the in-sample observations.

B.2 Surprises from Federal Funds Futures

SoonTM.

B.2.1 Surprises from Federal Funds Futures: Current Meeting

SoonTM.

B.2.2 Surprises from Federal Funds Futures: Next Meeting

SoonTM.

B.3 Surprises from Eurodollar Futures

SoonTM.

B.4 Surprises from Treasury Futures

SoonTM.