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Price Discovery on Modern Prediction Markets: Forecasting Federal Reserve Interest Rate Decisions

verfasst von / submitted by

Peter Pavicic BSc (WU)

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Matrikelnummer / student ID number: 11921713

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Betreut von / Supervisor: Assist. Prof. Dr. Felix Fattinger

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Contents

1	Introduction	6
2	Theoretical Framework	8
2.1	Prediction Markets	8
2.2	Polymarket	8
2.2.1	Introduction and Terminology	8
2.2.2	Order Matching	10
2.3	FedWatch Methodology	13
2.3.1	Effective Federal Funds Rate (EFFR)	13
2.3.2	CME 30-Day Federal Funds Futures	13
2.3.3	Assumptions	13
2.3.4	Months without an FOMC Meeting	14
2.3.5	Months with an FOMC Meeting	14
2.3.6	Risk-Neutral Probability Calculations	15
3	Data	17
3.1	Polymarket	17
3.1.1	Data Collection	17
3.1.2	Data Cleaning and Processing	18
3.2	30-Day Federal Funds Futures (ZQ)	19
3.3	Consolidated Data	19
4	Methodology	20
4.1	VAR and VECM	20
4.2	Removing Constant Series	21
4.3	Integration Order, Lag Order and Deterministic Terms	21
4.4	Johansen’s Procedure for Cointegration	21
4.5	Event-level Data: VECM	22
4.6	Pooled Data: VAR	23
4.7	Directional Granger Causality Testing	23
4.8	Instantaneous Causality	23
4.9	Rolling-window Granger causality (“which lags which”)	23
4.10	Robustness Checks	24
5	Results	25
5.1	Granger Causality	25
5.2	Instantaneous Causality	28
5.3	Which lags which	29
6	Discussion	31
7	Conclusion	33
8	Bibliography	34
A	ZQ and Polymarket implied probabilities	35
B	Robustness Check Results	47
B.1	Maximum-Eigenvalue Test Statistics	47
B.1.1	Granger Causality: Monday Excluded, 1 Minute Fidelity	47
B.1.2	Instantaneous Causality: Monday Excluded, 1 Minute Fidelity	49
B.1.3	Granger Causality: 5 Minute Fidelity	50
B.1.4	Instantaneous Causality: 5 Minute Fidelity	52

B.2	Trace Method Test Statistics	53
B.2.1	Granger Causality: 1 Minute Fidelity	53
B.2.2	Instantaneous Causality: 1 Minute Fidelity	55
B.2.3	Which lags which: 1 Minute Fidelity	56
B.2.4	Granger Causality: Monday Excluded, 1 Minute Fidelity	57
B.2.5	Instantaneous Causality: Monday Excluded, 1 Minute Fidelity	59
B.2.6	Granger Causality: 5 Minute Fidelity	60
B.2.7	Instantaneous Causality: 5 Minute Fidelity	62
C	Code	63

List of Figures

1	Polymarket front page on September 3rd, 2025	8
2	September FOMC event on Polymarket as of September 3rd, 2025	9
3	Continuous double auction in a market of the September FOMC event	10
4	A Polymarket market's orderbook	12
5	Proportion of observations removed from each Polymarket event dataset after data cleaning steps	18
6	Implied RN Probabilities February 2023 Meeting	35
7	Implied RN Probabilities March 2023 Meeting	36
8	Implied RN Probabilities May 2023 Meeting	36
9	Implied RN Probabilities June 2023 Meeting	37
10	Implied RN Probabilities July 2023 Meeting	37
11	Implied RN Probabilities September 2023 Meeting	38
12	Implied RN Probabilities November 2023 Meeting	38
13	Implied RN Probabilities December 2023 Meeting	38
14	Implied RN Probabilities January 2024 Meeting	39
15	Implied RN Probabilities March 2024 Meeting	39
16	Implied RN Probabilities May 2024 Meeting	40
17	Implied RN Probabilities June 2024 Meeting	40
18	Implied RN Probabilities July 2024 Meeting	41
19	Implied RN Probabilities September 2024 Meeting	41
20	Implied RN Probabilities November 2024 Meeting	42
21	Implied RN Probabilities December 2024 Meeting	43
22	Implied RN Probabilities January 2025 Meeting	44
23	Implied RN Probabilities March 2025 Meeting	45
24	Implied RN Probabilities May 2025 Meeting	45
25	Implied RN Probabilities June 2025 Meeting	46
26	Implied RN Probabilities July 2025 Meeting	46

Abstract

This master thesis asks whether a modern prediction market, Polymarket, or a traditional futures market reflects new information about upcoming Federal Open Market Committee decisions first. Prices are converted to risk-neutral implied probabilities aligned around meeting windows, and VECM-based Granger and instantaneous causality tools are used to evaluate lead-lag and contemporaneous cross-source effects. The core finding is two-way price discovery. Neither leads the other consistently, indicating complementary information aggregation. Results are robust to coarser (five-minute) sampling and weekend effects. The analysis contributes to a growing literature on modern prediction markets in an unprecedented context of a topic.

1 Introduction

Financial markets are known to aggregate information by turning private views into public prices, incorporating underlying private beliefs about the odds of potential future states of the world. Prediction markets make this explicit: in them, contracts are traded whose payoffs are tied to the outcome of distinct events. When the payoff is fixed to \$1 if state of the world realises, and \$0 otherwise, intuition dictates the trading price be read like a probability. While this seems appealing, it raises the question of what information these prices reflect. In other words, if they are read as probabilities, what probabilities are they measuring? This motivates the research topic of this thesis, the extent of price discovery in prediction markets.

This question could be explored in a multitude of ways. Since September 2024, prediction markets have enjoyed a surge in popularity due to the great volume in prediction markets related the 2024 US Presidential Election, with the highest volumes in prediction market history reached on modern prediction market platforms Polymarket and Kalshi. Multiple working papers are estimating the extent of price discovery through this market, such as in Ng et al. (2025), Cutting et al. (2025), and Jain et al. (2025). However, none are examining price discovery through Polymarket’s prediction market series on the interest rate decisions of the Federal Open Market Committee (FOMC), and comparing this to the price discovery of traditional financial markets’ futures data.

Prediction markets have been studied for three decades across political, corporate, and sports contexts, with a central topic of whether market prices can be read as forecasts of event probabilities. Wolfers and Zitzewitz (2004) synthesise early evidence from the Iowa Electronic Markets (IEM), sports-focused prediction markets, and commercial prediction markets. In Wolfers and Zitzewitz (2006) they go on to analytically derivative that, under risk-neutral pricing, contract prices can be interpreted as robust estimates of average beliefs about probabilities. Arrow et al. (2008) agree with this perspective in their article published in the *Science* journal, and call for government regulation to harness potential scientific benefits in small cap prediction markets. Berg et al. (2008) analyse US presidential election histories between 1988 and 2004 hosted by the IEM and find that prices are consistently well-set and estimates viewed as probabilities are competitive with standard, traditional political forecasting benchmarks. Cowgill and Zitzewitz (2015) take a different approach in studying markets internal to corporations, such as at Google, Ford, and a third, anonymous firm, finding that prices track subsequent realisations fairly well and even outperform expert estimates in mean-squared error metrics and attribute this success to market mechanisms.

Another, still political but economics-focused strand of literature, concerns itself with using prediction markets’ probabilities as proxies of public and investor sentiment. This literature examines potential information from prediction markets when combined alongside traditional financial markets. Leigh et al. (2003) present a case study on the Iraq war which uses prediction market prices as conflict probabilities and compares them to price movements in oil, equities, and other asset classes. Snowberg et al. (2007) use prediction markets to infer who the public thought was going to win the 2000 and 2004 US presidential elections. The events’ price-implied probabilities of a Republican or Democratic potential winner are paired with futures data, which reflect similar expected economic impacts.

A third, more recent strand of literature focuses on microstructural and arbitrage considerations regarding prediction markets. Saguillo et al. (2025) conduct a large-scale arbitrage study on Polymarket, using on-chain order-book data together with LLM-powered arbitrage detection to analyse systematic price inconsistencies and realised arbitrage profits. Ng et al. (2025) consider cross-platform (Polymarket and Kalshi) arbitrage opportunities and price discovery by deep-pocketed market participants during the last days of the largest prediction market event in history as of writing this thesis, the 2024 US Presidential election.

Across these literatures, methods vary with the question. In research related to efficiency and accuracy, researchers rely on calibration curves scoring rules. In market-microstructure and mispricing, the latest Polymarket research uses algorithmic detection. Where prediction markets are combined with traditional assets, event studies and factor-style decompositions are prevalent.

This thesis relates to these three main strands of literature, addressing a gap where all of them meet: a one-to-one, high-frequency comparison of modern prediction market probabilities and prices in a directly corresponding, liquid futures market to address the question of market efficiency. Much of the classic efficiency and accuracy evidence aggregates average forecast performance. Studies that connect prediction markets to financial assets typically use short cross-sectional event windows. From a data perspective, high-volume prediction markets exist on Polymarket for every Federal Open Market Committee (FOMC) interest rate decision, yet no research has been done on this topic.

Minute-by-minute price discovery is analysed by continuously matching prediction market contracts to derivatives traded on the Chicago Mercantile Exchange that price the same event. By converting granular Polymarket and 30-Day Federal Funds rate futures into risk-neutral price-implied probabilities and testing for short-horizon price discovery, the thesis provides an assessment of whether prediction markets lead traditional ones in incorporating news about FOMC outcomes. The econometric methodology aligns with standard practice in financial time-series analysis, drawing on the VECM framework, Johansen methodology, and Granger as well as instantaneous causality tests to single out, examine, and compare short-run price-adjustment.

2 Theoretical Framework

2.1 Prediction Markets

For the purposes of this thesis, prediction markets are defined as financial markets designed to forecast future events. Participants of prediction markets trade state-contingent claims whose payoff depends on how those future events unfold. While different types of prediction markets have been designed, the scope of this thesis is limited to “winner-take-all” prediction markets as defined in Wolfers and Zitzewitz (2004). These markets are typically structured in the following way: a claim costs $\$p$ today and pays $\$1$ if and only if the stated event occurs, and $\$0$ otherwise. This structure implies two participants agreeing on the price $\$p$ which one of the participants pays, the other putting up $\$(1 - p)$, with the winner receiving the $\$1$ put up in collateral as their payoff.

Through price discovery, traditional financial markets aggregate information about the value of assets. Following Berg et al. (2008), prediction markets’ primary purpose is leveraging this role of markets for forecasting. Under the Efficient Markets Hypothesis, the market price on prediction markets should reflect the risk-neutral probabilities of the event in question, encompassing all available information. As indicated in Section 1, this thesis examines the prices of the modern prediction market Polymarket in its analysis to infer the degree of price discovery by comparing its price movements to those in traditional futures data.

2.2 Polymarket

2.2.1 Introduction and Terminology

This section introduces concepts and terminology used on Polymarket. Unless indicated otherwise, the sources for this information are the Polymarket website¹ itself, or the site’s documentation².

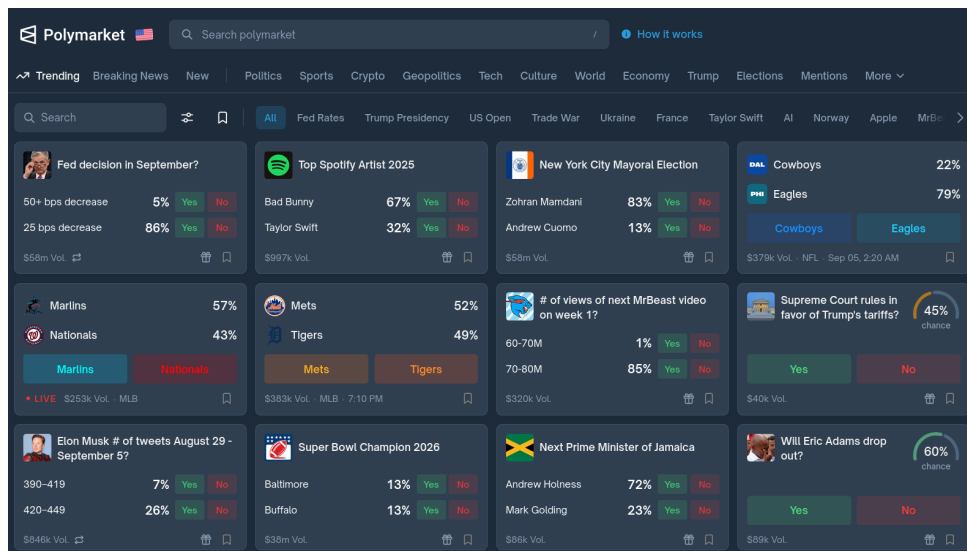


Figure 1: The Polymarket front page as of September 3rd, 2025

Polymarket, depicted in Figure 1, is one of the world’s largest prediction market-hosting platforms. On it, prediction markets are grouped into “events”, which contain different “markets” related to a single topic/occasion. While anyone can propose an event through social media

¹<https://polymarket.com/>

²<https://docs.polymarket.com/>

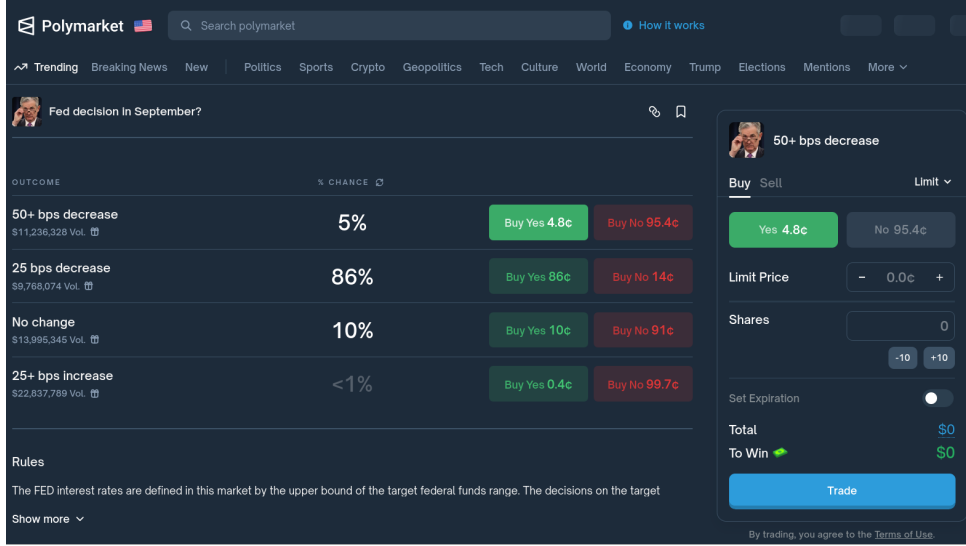


Figure 2: September FOMC event on Polymarket as of September 3rd, 2025

The figure shows Polymarket’s September FOMC event page. This event contains 4 possible markets. Each market related to possible interest rate decisions (50+ bps increase, 25 bps decrease, No change, 25+ bps decrease) is grouped here, making it simpler for traders to compare prices across markets.

channels such as Discord and Twitter/X, Polymarket retains the right to create events themselves. Each “market” is a winner-take-all market as outlined in Section 2.1, and concerns itself with exactly one “question” regarding the outcome of the event it is a part of. Market participants can trade on these questions by buying or selling existing shares in binary “Yes” and “No” claims i.e. $C \in \{\text{Yes}, \text{No}\}$ (called “outcomes” or “outcome shares”), with prices for each of these shares, $P(C) \in [0, 1]$. When an event concludes, its markets are “resolved”, meaning the claims of the outcome which realised in the world C^* in each market can be converted to \$1 per claim, with claims in the opposite outcome, $(C^*)'$, realising a \$0 payoff. This resolution happens according to rules stipulated for every event, which are designed to provide clarification on the markets’ questions, in order to avoid situations where no market could resolve to a “Yes” outcome, despite being designed in such way.

Figure 2 shows the FOMC interest rate decision event for September, 2025, which features 4 markets regarding the potential interest rate decisions. These markets are non-overlapping and exhaustive, meaning one and only one of the markets will resolve to “Yes”, while the other markets resolve to “No”. This is ensured by the rules, which for this market are the following:

The FED interest rates are defined in this market by the upper bound of the target federal funds range. The decisions on the target federal fund range are made by the Federal Open Market Committee (FOMC) meetings. This market will resolve to the amount of basis points the upper bound of the target federal funds rate is changed by versus the level it was prior to the Federal Reserve’s September 2025 meeting. If the target federal funds rate is changed to a level not expressed in the displayed options, the change will be rounded up to the nearest 25 and will resolve to the relevant bracket. (e.g. if there’s a cut/increase of 12.5 bps it will be considered to be 25 bps) The resolution source for this market is the FOMC’s statement after its meeting scheduled for September 16 - 17, 2025 according to the official calendar:
<https://www.federalreserve.gov/monetarypolicy/fomccalendars.htm>.

The level and change of the target federal funds rate is also published at the official website of the Federal Reserve at <https://www.federalreserve.gov/monetarypolicy/openmarket.htm>.

This market may resolve as soon as the FOMC’s statement for their September meeting with relevant data is issued. If no statement is released by the end date of the next scheduled meeting, this market

will resolve to the "No change" bracket.

2.2.2 Order Matching

As Figure 2 shows, market participants can submit limit or market orders to buy or sell Yes or No claims. While buying is allowed at any quantity, short selling is not permitted on Polymarket, and only owned shares can be sold. This results in some price-inefficiencies, such as in Figure 2, where despite the exhaustive set of markets, for each market i in the set of markets in that event, I , the bid prices exhibit $\sum_{i \in I} P_i(\text{Yes}) \neq \1 , $\sum_{i \in I} P_i(\text{No}) \neq \3 , as well as $\sum_{i \in I} (P_i(\text{Yes}) + P_i(\text{No})) \neq \4 . This, however, is not exploitable due to lack of short-selling. As explained in Section 2.1, a trade is only possible if two individual market participants agree on a price, which is why on Polymarket, it is mechanically ensured that $P(C) + P(C') = \$1$ for any two complementary claims (opposite outcomes). This guarantees that every pair of claims $(C, C') \in \{\text{Yes}, \text{No}\}$ is necessarily fully collateralised by \$1, put up by the holders of the "Yes" and "No" shares, ensuring the successful resolution of the market.

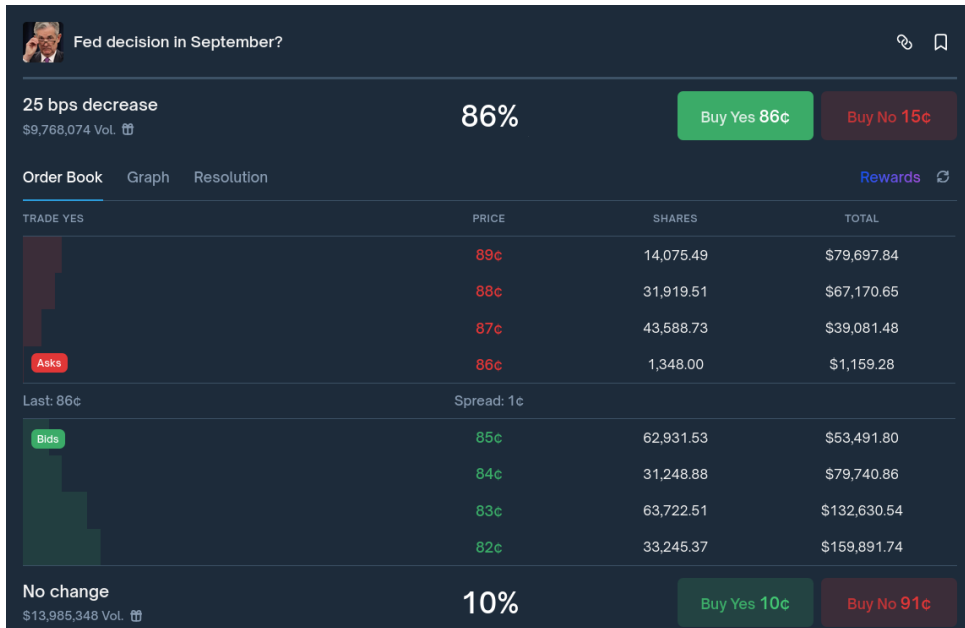


Figure 3: Continuous double auction in a market of the September FOMC event

This figure shows the limit order book for Polymarket’s prediction market for the event that in September 2025, the FOMC decides to lower the upper bound federal funds rate by 25 basis points. Each row specifies the prices in the limit order book, the number of shares which can be traded at the given price or closer to the midpoint (in the Shares column), as well as the cumulative totals of the orders (in the Total column)

Trading on Polymarket takes form in a continuous double auction, with no halts in trading between a market’s opening and its resolution. This is shown in Figure 3, with resting bid and ask limit orders being displayed for “Yes” outcome claims in the market for the FOMC meeting in September to conclude with a 25 bps decrease in the upper bound of the target federal funds range.

Mechanically, this is realised on Polymarket’s centralised limit order book (CLOB) which has a “hybrid” organisation of off-chain order matching, and on-chain settlement. This entails that market participants’ orders are submitted to the CLOB, hosted on Polymarket servers,

where they are matched into trades. Once a trade has been recorded on the servers, the actual settlement, execution, and recording of transactions takes place on the Polygon blockchain. While an in-depth description of the blockchain mechanism is beyond the scope of this thesis, the key implication is that all trades on Polymarket are publicly available, with identifiable users. Internally, pairs of opposing outcome shares (C, C') are represented by pairs of “binary outcome tokens”, which are pairs of Yes and No claims in the same market, created upon being exchanged for and collateralised by the same nominal amount of “USDC”, the underlying currency for all exchange taking place on Polymarket. USDC is a cryptocurrency (a stablecoin), which is pegged to the United States dollar, and has been since 2021 accepted in transaction settlement by payment services provider Visa (Hussain, 2021). For the purposes of this thesis, “USDC” will be referred to in terms of US dollars ($1 \text{ USDC} = 1 \text{ USD}$), while the term “outcome token” may be used to refer to digital assets representing a single share in a claim. The effects of Polymarket’s internal mechanisms on data acquisition is elaborated on in Section 3.1.

There are three distinct possibilities by which market participants’ orders are matched. This is established in the Polymarket exchange’s source code³ and follows the terminology of Saguillo et al. (2025):

Direct trade A marketable order (by a liquidity taker) in a given claim C matches resting liquidity providing (maker) orders in the same claim C . Here, one side is selling the claim C , while their counterparty in the trade is buying that same claim. Internally, settlement is a straightforward token-for-USDC swap at the matched price. This order-matching mechanism is essentially identical to the one familiar from traditional equities markets.

Minting new tokens Because a pair of opposite outcome tokens (C, C') are always backed by \$1 of collateral, two buy orders from opposite-token orderbooks can also be matched if they agree on the price. In this case, new sets of binary outcome tokens are created, a process referred to as ‘minting’, where each pair of outcome tokens (C, C') is backed by \$1 put up cumulatively by the counterparties of the trade. Terminologically it can also be said that each dollar of collateral is ‘split’ into a pair of outcome tokens. This happens when there exists a resting limit buy order (a bid) for the claim C with price $P(C) =: p$, which is then matched with an incoming marketable buy (another bid) of the same size for the opposite claim C' with price $P(C') = 1 - p$.

Burning tokens The reverse operation of minting, this operation eliminates a set of outcome tokens (C, C') from the market and releases the collateral which was used to back it. This happens when two sell orders in opposite tokens’ orderbooks sum such that the number of pairs of outcome tokens matches the amount of USDC cumulatively demanded, for them, i.e. when a resting sell order (an ask) for C wishes to sell at price $P(C) =: p$, which is matched by an incoming marketable sell order of C' of the same size at price $P(C') =: 1 - p$. The set of tokens (C, C') are burned (or ‘merged’), and each side receives the collateral that had been initially put up when the tokens were minted.

Visually, as shown in Figure 4, limit orders in orderbooks of a pair of outcome tokens (C, C') are represented symmetrically, i.e. bids (resp. asks) in C will be shown as asks (resp. bids) in C' , and vice versa. This follows the logic described above, since any of the three options for order matching appear the same to market participants. It can be seen that nearest to the spread, opposite-side orders in opposite outcome tokens are equal in amount and their total sums to the number of shares involved. This is explained by the fact that bid orders in “Yes” tokens are also listed as ask orders in “No” tokens and vice versa. While this observation only holds for best bid and best ask entries, it can be shown that this is the same deeper into the limit order book. This is not immediately obvious as the “Total” column displays the total amounts

³<https://github.com/Polymarket/ctf-exchange/>

SHARES	TOTAL	PRICE	SHARES	TOTAL
14,075.49	\$79,697.84	89¢	33,245.37	\$31,256.54
31,919.51	\$67,170.65	88¢	63,722.51	\$25,272.38
43,588.73	\$39,081.48	87¢	31,248.88	\$14,439.55
1,348.00	\$1,159.28	86¢	62,931.53	\$9,439.73
Yes Orders			No Orders	
62,931.53	\$53,491.80	85¢	1,348.00	\$188.72
31,248.88	\$79,740.86	84¢	43,588.73	\$5,855.25
63,722.51	\$132,630.54	83¢	31,919.51	\$9,685.60
33,245.37	\$159,891.74	82¢	14,075.49	\$11,233.90

Figure 4: A Polymarket market’s orderbook

The figure shows a collage of the limit order book in the “25 bps decrease” market for the September FOMC decision event on Polymarket, taken on September 3rd, 2025. The collage contains the limit order book of both the Yes and No tokens, at the 8 nearest prices to the midpoint. The “Shares” column shows the number of tokens which could be traded at the price given by “Price” or closer to the midpoint. Similarly, the “Total” columns show the cumulative USDC value of open interest at or at prices closer to the midpoint than the corresponding row’s price.

cumulatively, i.e. the amount that can be spent to get the respective shares at the respective prices or at better prices, e.g. If one sells “No” orders, \$5885.25 can be sold above the price of 84 cents.

Each of the order-matching mechanisms work based on the necessary condition that $P(C) + P(C') = \$1$, which underlies winner-take-all markets. It is important to note that this is the only arbitrage-eliminating mechanism implemented internally, and that this only works on the level of markets, not events. Since events are just collections of markets, there is no internal mechanism to prevent arbitrage across markets, such as $\sum_{i \in I} P_i(\text{Yes}) \leq \1 , $\sum_{i \in I} P_i(\text{No}) \leq \$N - 1$, as well as $\sum_{i \in I} (P_i(\text{Yes}) + P_i(\text{No})) \leq \N , where i is a market in the set of markets for a given event I which contains N number of markets.

Additionally, the split/merge operations (minting and burning tokens) are not restricted to order matching. Users may themselves at any time during the market’s lifetime split units of USDC into pairs of binary outcome tokens (C, C') , ‘buying’ each for \$0.50, or merge a pair of tokens to receive the underlying collateral. The former can be useful to market participants who wish to act as market makers, while the latter can be used to liquidate large positions over time without moving markets too heavily.

2.3 FedWatch Methodology

This section explains the methodology for arriving at the futures market’s price-implied risk-neutral probabilities of FOMC decisions for each scheduled meeting. This is referred to as the CME “FedWatch” methodology, described on the relevant website⁴ by the Chicago Mercantile Exchange, which is the main source for this section, unless specified otherwise.

2.3.1 Effective Federal Funds Rate (EFFR)

The effective federal funds rate (EFFR) is the volume-weighted median interest rate on uncollateralised overnight loans of US dollar reserve balances between depository institutions in the United States. The Federal Reserve Bank of New York computes the EFFR and publishes it on their website⁵ for the previous business day at approximately 9:00AM New York time every day. The monthly arithmetic average of this benchmark rate is the underlying asset of the Chicago Mercantile Exchange’s (CME’s) 30-Day Federal Funds futures.

2.3.2 CME 30-Day Federal Funds Futures

CME 30-Day Federal Funds futures are futures contracts traded on the ZQ ticker, which trade on the realised monthly arithmetic average EFFR for a given month. They are monthly contracts listed for 60 months in advance, with the intended purpose (as per CME⁶) of hedging short-term interest rate risk. Trading of a contract stops on the last business day of the maturity month, and settlement occurs in cash on the next business day. ZQ futures prices are quoted in International Monetary Market (IMM) index terms, where the price is given as 100 minus the implied average daily EFFR in the contract’s calendar month. Formally, let P_t^T denote the price of the futures contract for month T at timepoint t . Then:

$$\mathbb{E}_t[\bar{r}_T] = 100 - P_t^T \quad (1)$$

\bar{r}_T denotes the arithmetic average of daily EFFR realisations during month T , while $\mathbb{E}_t[\cdot]$ denotes $\mathbb{E}[\cdot|\mathcal{F}_t]$, i.e. the risk-neutral conditional expectation of the argument \cdot given the filtration at timepoint t (the information available at t). $\mathbb{E}_t[\bar{r}_T]$ here is the risk-neutral expectation of the underlying implied by the price P_t^T .

2.3.3 Assumptions

To translate ZQ prices into risk-neutral probabilities of outcomes of FOMC meetings, the CME has developed its “FedWatch” tool, which performs this exact calculation based on daily closing prices. These probabilities are often reported in financial news and media when reporting markets’ expectations regarding upcoming FOMC meetings’ outcomes.

The tool adopts five core assumptions:

1. Interest rate changes happen only at scheduled FOMC meetings (no surprise meetings). There is either no meeting or one meeting in a month.
2. Interest rate changes occur in uniform 25 basis point increments, i.e. in amounts divisible by 25 basis points (bps).
3. The EFFR adjusts proportionally to the target change. This implies if there is a change of Δ in the Federal Reserve’s target range, the EFFR also changes by Δ , where Δ must be divisible by 25 bps.

⁴<https://www.cmegroup.com/articles/2023/understanding-the-cme-group-fedwatch-tool-methodology.html>

⁵<https://www.newyorkfed.org/markets/reference-rates/effr>

⁶<https://www.cmegroup.com/markets/interest-rates/stirs/30-day-federal-fund.html>

4. Within a meeting month, the EFFR is piecewise constant: it equals a pre-meeting level up to the decision’s effective date, and a post-meeting level thereafter.
5. The EFFR at the end of a given month equals the EFFR at the start of the month thereafter. Formally, for any month T : $r_T^{\text{End}} = r_{T+1}^{\text{Start}}$

Under these assumptions, the FedWatch tool calculates a risk-neutral expectation of the future path of the EFFR from the prices of the 30-Day Federal Funds futures at different maturities. The jumps in this discontinuous expected path signify changes in the EFFR, and therefore changes in the Federal Reserve’s target range. For expected jumps that are not in exact 25 bp increments, the jump amount is written as the linear interpolation of two possible jumps, where the weights represent the risk-neutral implied probabilities. This method is elaborated in the next sections.

This thesis replicates this FedWatch methodology for use on minute-by-minute data.

2.3.4 Months without an FOMC Meeting

In any month with no scheduled FOMC meeting, under the assumptions outlined in Section 2.3.3, the Federal Reserve’s target range and therefore the EFFR do not change for the entire calendar month. The FedWatch method calls these months without a meeting “anchor months”. Let r_T^{Start} and r_T^{End} denote the EFFR at the start resp., at the end of month T . For an anchor month T it holds that:

$$\mathbb{E}_t[r_{T-1}^{\text{End}}] = \mathbb{E}_t[\bar{r}_T] = \mathbb{E}_t[r_{T+1}^{\text{Start}}] \quad (2)$$

Since $\mathbb{E}_t[\bar{r}_T] = 100 - P_t^T$ is known, Equation 2 explains how price-implied expected rates can propagate to preceding and succeeding months given the price of the futures contract which for month T .

In applying the methodology for month T , one identifies the nearest anchor month, determines the implied expected rate from its ZQ futures price using Equation 1, sets the expected rates for the end of the prior month and the start of the following month to that level, and then propagates these values backward and forward as needed when solving adjacent meeting months.

2.3.5 Months with an FOMC Meeting

For a meeting month T , let n_T denote the number of calendar days before the interest rate policy decision made at the meeting becomes effective for a full day. Since FOMC meetings last two days, and the meeting’s interest rate decision is announced on the second day of the meeting at 14:00 Eastern Time, n_T includes both the first and the second day of the meeting. Let m_t denote the remaining number of calendar days in the month, such that $n_T + m_T$ gives the number of calendar days of month T .

Note that since there can only be one meeting per month, the pre-meeting EFFR level is unchanged from the end of the previous month, r_{T-1}^{End} and the post-meeting level would remain until the start of the next month, r_{T+1}^{Start} .

Because $\mathbb{E}_t[\bar{r}_T]$ is the expected arithmetic monthly average, it can be written as a linear interpolation of the pre- and post-meeting levels:

$$\mathbb{E}_t[\bar{r}_T] = \omega_T \mathbb{E}_t[r_{T-1}^{\text{End}}] + (1 - \omega_T) \mathbb{E}_t[r_{T+1}^{\text{Start}}], \quad \omega_T := \frac{n_T}{n_T + m_T} \quad (3)$$

Rearranging for the expected pre-meeting (beginning-of-month) resp., post-meeting (end-of-month) level gives:

$$\mathbb{E}_t[r_{T-1}^{\text{End}}] = \frac{1}{\omega_T} (\mathbb{E}_t[\bar{r}_T] - (1 - \omega_T)\mathbb{E}_t[r_{T+1}^{\text{Start}}]) \quad (4)$$

$$\mathbb{E}_t[r_{T+1}^{\text{Start}}] = \frac{1}{1 - \omega_T} (\mathbb{E}_t[\bar{r}_T] - \omega_T\mathbb{E}_t[r_{T-1}^{\text{End}}]) \quad (5)$$

When the following month $T + 1$ is an anchor, using Equations 2 and 1:

$$\mathbb{E}_t[r_{T+1}^{\text{Start}}] \stackrel{\text{Eq.2}}{=} \mathbb{E}_t[\bar{r}_{T+1}] \stackrel{\text{Eq.1}}{=} 100 - P_t^{T+1} \quad (6)$$

The same logic applies when the previous month $T - 1$ is an anchor, with

$$\mathbb{E}_t[r_{T-1}^{\text{End}}] = \mathbb{E}_t[\bar{r}_{T-1}] = 100 - P_t^{T-1} \quad (7)$$

Since ZQ futures prices are available for every month, $\mathbb{E}_t[\bar{r}_T] = 100 - P_t^T$ is known for all months T . This means Equation 3 can always be solved for either $\mathbb{E}_t[r_{T-1}^{\text{End}}]$ or $\mathbb{E}_t[r_{T+1}^{\text{Start}}]$, in case either the previous or following month is an anchor month. This is due to the fact that of the three risk-neutral expected rates, two can always be backed out from futures prices using Equation 1.

When neither the following, nor the previous months are anchor months, the nearest anchor month in the future T_A is found. Then Equations 2 and 3 are used to solve for $\mathbb{E}_t[r_{T_A-1}^{\text{Start}}]$. According to the assumptions explained in Section 2.3.3, $\mathbb{E}_t[r_{T_A-1}^{\text{Start}}] = \mathbb{E}_t[r_{T_A-2}^{\text{End}}]$ and using Equation 3, this process is repeated until the current month T is reached.

Given the term structure of the futures contracts then, for all meeting months T , the pre- and post-meeting levels can be computed. This means the jump induced by the FOMC meeting's decision can be estimated, which is the risk-neutral expected change in the EFR.

2.3.6 Risk-Neutral Probability Calculations

The FedWatch method employs a method referred to as “characteristic-mantissa method” to arrive at the risk-neutral probabilities of the rate cuts possible under the FedWatch assumptions (in 25 bp increments). The essence of this method lies in thinking of the risk-neutral expected change as a linear interpolation of the two nearest full 25 bp increment changes. The weight of each is then the risk-neutral probability associated with that possible change. As an example, if the expected change is 29 basis points, this is written as $29 = P^*(\text{change} = 25)25 + P^*(\text{change} = 50)50 = \frac{4}{25}25 + \frac{21}{25}50 \implies P^*(\text{change} = 25) = \frac{4}{25}, \quad P^*(\text{change} = 50) = \frac{21}{25}$.

More formally, define the risk-neutral expected change in EFR over the meeting month as

$$\Delta_T^* := \mathbb{E}_t[r_T^{\text{End}}] - \mathbb{E}_t[r_T^{\text{Start}}] = \mathbb{E}_t[r_{T+1}^{\text{Start}}] - \mathbb{E}_t[r_{T-1}^{\text{End}}] \quad (8)$$

Express this in units of 25 bps, $k_T^* := \Delta_T^*/0.0025$. Decompose k_T^* into its characteristic (integer) and mantissa (fractional) parts:

$$k_T^* = k_T + y_T, \quad k_T \in \mathbb{Z}, 0 \leq y_T < 1. \quad (9)$$

This is achieved by setting:

$$k_T := \lfloor k_T^*/25 \rfloor \tag{10}$$

$$y_T := k_T^* - k_T \tag{11}$$

Where k_T is the lower bound for the number of 25 bp rate changes, and $k_T + 1$ is the upper bound.

The two possible outcomes at the meeting in month T are then: a change of $k_T \cdot 25$ bps with risk-neutral probability $1 - y_T$, and a change of $(k_T + 1) \cdot 25$ bps with risk-neutral probability y_T .

3 Data

This section documents the collection and preparation of the data used in the empirical analysis. This consists of two datasets: transaction-level data from Polymarket for every FOMC event hosted before September 2025 and 30-Day Federal Funds Rate futures (ZQ) data at 1-minute fidelity. These are collected and transformed separately and are then pooled to a common intraday grid to construct aligned price-implied risk-neutral probability timeseries data before unit-root, cointegration and Granger causality testing. These latter procedures are described in Section 4.

3.1 Polymarket

3.1.1 Data Collection

After trading orders are matched, as described in Section 2.2.2, trades on Polymarket are recorded on the Polygon blockchain. Since reading raw blocks from a blockchain is rather cumbersome, Polymarket provides “subgraphs”, which are databases which continuously convert blockchain data into a queryable format. These subgraphs are hosted online by GoldSky, and makes various Polymarket data (users’ positions, transactions, users’ PnL, market data) available through a public API. This makes it possible to parse blockchain data using the highly abstract GraphQL language without handling low-level blockchain details. The main source for this section is the documentation at the API’s link⁷, as well as the source code⁸.

Trade execution on Polymarket’s hybrid CLOB produces distinct on-chain events. All 3 types of order matches described in Section 2.2.2 emit an OrderFilled event. These events are queryable on the “OrderBook” subgraph. The analysis relies on data acquired from this subgraph since it records every executed trade with a timestamp and token identifier, which are sufficient to reconstruct price series at tick-by-tick frequency.

A Python querying script is implemented to gather OrderFilled events from the “OrderBook” subgraph via queries written in GraphQL. The script constructs parameterised queries for each FOMC event’s markets and each of their two outcome tokens (Yes/No). For every market, the query filters for fills where the outcome token traded is the relevant Yes or No token and requests results be ordered by ascending timestamp. At once only up to 1000 OrderFilled events can be fetched, therefore, pagination is implemented by injecting GraphQL variables “\$skipN” and “\$firstN” into the query text so that batches of 1000 rows can be fetched iteratively in an automated way. Each page’s raw JSON response is saved to disk to create a complete archive for offline processing.

Since each query’s results need to be organised such that they can be linked back to FOMC events and their respective markets, a list of relevant markets and tokens is created by accessing market metadata from the Gamma Markets API. The Gamma API is hosted by Polymarket, which organises metadata, such as titles and identifiers for events and markets, internal data, such as event descriptions, icons, as well as metrics of volume, competitiveness, and liquidity, and other information not relevant in the scope of the thesis.

For this, FOMC event identifiers (IDs, known internally as “slugs”) are collected manually. Metadata (market titles and the ERC-1155 token IDs that identify the Yes and No assets) are then obtained via the Gamma API and used to bind token IDs to human-readable asset names. A table built for this purpose maps each token ID to its human-readable asset name, the event ID, and the human-readable event title.

⁷https://api.goldskey.com/api/public/project_cl6mb8i9h0003e201j6li0diw/subgraphs/orderbook-subgraph/

⁸<https://github.com/Polymarket/polymarket-subgraph>

3.1.2 Data Cleaning and Processing

Batches of JSON files with 1000 entries each are converted into combined per-token csv files. These are read and re-aggregated at the market-level and event-level. For each FOMC event, trades are sorted chronologically and grouped by market (a pair of Yes-No tokens).

Recorded transactions involving “No” assets are converted into equivalent trades in the “Yes” token, to ensure the highest level of fidelity. Duplicate entries (such as in the case of order fills which result from minting new tokens) are removed. Since each record contains prices and timestamps for a single trade in a single asset, these are converted into timeseries data, where each observation reflects the last-traded prices in each asset.

The result is a per-event timeseries data with recorded time and the most recent Yes asset’s (or converted No asset’s) price measured in dollars. These prices are economically interpreted as risk-neutral probabilities for the given interest rate decision realising at the underlying FOMC meeting.

An interesting feature of the dataset is that, price-implied probabilities of all assets for a given event often exceed 1. It can be argued that this happens due to the absence of short-selling, which would incentivise traders to pursue arbitrage trading by selling at market prices and buying the winning outcome back after the FOMC meeting happens, before the market closes.

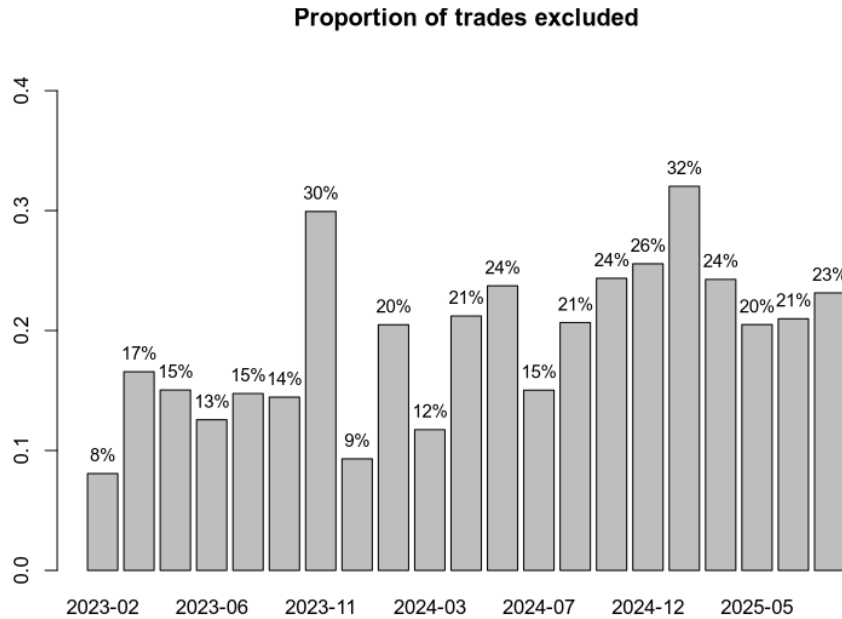


Figure 5: Proportion of observations removed from each Polymarket event dataset after data cleaning steps

The futures market is closed on weekends whereas Polymarket trading occurs around the clock, including weekends. To make the sources comparable, weekend observations are removed from the Polymarket timeseries. Since some early minutes in the examined events exhibit very little trading and low sums of asset prices, all observations where the sum of outcome prices falls below a threshold of \$0.2 are additionally discarded. This only happens at the beginning of datasets and is done to prevent its influence on the results of the Granger causality tests.

Figure 5 shows the proportion of observations excluded after these steps compared to before

they are performed. While these steps in some cases reduce the number of observations greatly, the desired statistical tests are not economically interpretable without doing so.

3.2 30-Day Federal Funds Futures (ZQ)

Intraday ZQ historical prices are retrieved from TradingView and Barchart. TradingView provide sufficient minute-level data up until September 2024, however, from then onwards until September 2025, early futures data is missing. Data from Barchart is therefore used for these markets, and the data available from TradingView is used to check for data completeness and integrity. The two sources are manually converted into uniform format with timestamps in New York time and respective closing prices.

The methodology for extracting risk-neutral probabilities from prices of ZQ futures follows Section 2.3. In the implementation, the contracts relevant for each meeting are first joined into a single table. For each meeting month, start-of-month or end-of-month implied rates are computed as needed. Potential interest rate decisions and their risk-neutral probabilities are calculated for the same set of discrete outcomes used on Polymarket (e.g. up25, noChange, down25).

The resulting dataset contains a table each for the 21 FOMC decisions observed. Each of the tables contains a timeseries of risk-neutral probabilities at tick-by-tick frequency (of the ZQ futures data) on weekdays. Since these are price-implied risk-neutral probabilities, their sum always adds up to 1.

3.3 Consolidated Data

To align data from both sources, a common one-minute timegrid (excluding weekends) is created per observed meeting. The start and end of each grid are set to the timespan of the Polymarket data. Data from both Polymarket and ZQ sources are merged into these datasets in the following way: Raw timestamps from each dataset are rounded up to the next full minute. Where multiple observations are present, the last ones are kept. Remaining gaps are filled using last-observation-carried-forward so that every minute contains a probability for each asset from both sources. Every one of the event-level datasets' timeseries is shown in Appendix A.

Additionally, a pooled dataset is constructed. This is done by choosing the two decisions for each meeting, which have the highest mean implied probability in the ZQ data over the merged data for that meeting. The data is then pooled by rolling continuously over each dataset, always considering the data for the nearest meeting.

4 Methodology

This section develops the econometric framework used, that is examining whether prediction-market risk-neutral probabilities and futures-implied risk-neutral probabilities around Federal Open Market Committee (FOMC) decisions could be useful to predict one another. The notation and explanation of this section, unless indicated otherwise, follows Lütkepohl (2005) and Verbeek (2017). The analysis proceeds for both the per-event and pooled datasets mentioned in Section 3.3. In the per-event dataset, for each FOMC event, a multivariate system is formed which contains between one and for outcome each for Polymarket and the 30-Day Federal Funds Rate futures (ZQ), aligned at one-minute frequency. Meanwhile the pooled dataset concatenates all event windows into a four-variable system (with the Polymarket and ZQ timeseries for the highest-probability decisions according to ZQ futures throughout the lifetime of the corresponding Polymarket event).

4.1 VAR and VECM

Let $Y_t \in \mathbb{R}^K$ denote observations at time t within a given event window, partitioned by source as

$$Y_t = \begin{pmatrix} Y_t^{(PM)} \\ Y_t^{(ZQ)} \end{pmatrix}, \quad Y_t^{(PM)} \in \mathbb{R}^m, \quad Y_t^{(ZQ)} \in \mathbb{R}^n, \quad K = m + n \quad (12)$$

where $m \in 1, \dots, 4$ and $n \in 1, \dots, 4$ are the numbers of non-constant outcome series retained (after the filtering explained in Section 4.2) from Polymarket (PM) and ZQ, respectively. Typical outcomes include up25, noChange, down25, and down50.

For the pooled analysis, the system consists of $K = 4$ with two Polymarket ($n = 2$) and two ZQ ($m = 2$) series.

The general VAR(p) representation for data in levels is

$$Y_t = A_1 Y_{t-1} + \dots + A_p Y_{t-p} + \Phi D_t + u_t, \quad u_t \sim WN(0, \Sigma_u) \quad (13)$$

where $A_i \in \mathbb{R}^{K \times K}$ are autoregressive coefficient matrices, D_t denotes deterministic terms, and u_t are innovations with covariance Σ_u . When components of Y_t are integrated and cointegrated, the equivalent VECM representation is

$$\Delta Y_t = \Pi Y_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \Delta Y_{t-i} + \Phi^* D_t + u_t, \quad \Pi = \alpha \beta', \quad \text{rank}(\Pi) =: r \quad (14)$$

with $\beta \in \mathbb{R}^{K \times r}$ the cointegrating vectors, $\alpha \in \mathbb{R}^{K \times r}$ the adjustment coefficients, and r the cointegration rank.

The methodological sequence performed on the two datasets is as follows:

1. Removal of constant series
2. Integration order estimation
3. VAR model selection (lag order, inclusion of deterministic terms)
4. * Cointegration rank determination by Johansen's maximum eigenvalue method
5. * Estimation of error correction terms (ECTs)
6. * Model reselection for VECM (lag order, deterministic terms)

7. * Construction of VECM
8. Granger causality testing in both directions
9. Instantaneous causality testing
10. Rolling-window Granger causality testing to determine the extent of Granger Causality in each direction
11. Robustness checks

where the steps marked with * are left out for the pooled dataset. In this case, the Granger causality test is performed on the estimated VAR, while for the event-level dataset, it is performed on the VECM.

4.2 Removing Constant Series

Within some event windows, certain outcome series are exactly constant. Most commonly these are Polymarket outcomes in early markets which never trade and remain at zero, or (more common) ZQ-implied outcomes which remain flat throughout the event windows. Exactly constant series are removed before any testing. The reason is purely mathematical: the sample second-moment matrices that enter the reduced-rank eigenvalue problem must be non-singular. Including a constant column would result in singular matrices. This also makes sense economically, since constant series do not carry additional information, their removal has no effect on inference about the remaining variables.

4.3 Integration Order, Lag Order and Deterministic Terms

The order of integration determines whether inference proceeds in levels or differences and whether checking for cointegration is relevant. In each event-level system, ADF-tests show that retained series are overwhelmingly non-stationary in levels and stationary in first differences. This matches economic intuition: As the true outcome becomes more and more obvious, the timeseries for the realised outcome tend toward a probability of 1 and toward 0 for the rest. The differenced data, however, does not display such properties, making them once-integrated or $I(1)$. For reasons of simplicity and uniformity, all series in every event window of this type of data are treated as $I(1)$. ΔY_t is stationary and a VECM is the appropriate vehicle for inference in this case. Since the levels are non-stationary, a check for cointegration is in order. For the pooled dataset, the concatenated timeseries are stationary in levels. In this case, the series are accordingly treated as $I(0)$ and a VAR is sufficient for modelling. Cointegration is not relevant in this case.

Lag orders for all VAR and VECM models are chosen using the Schwarz Information Criterion (aka BIC).

The inclusion of deterministic terms in relevant VAR and VECM models is determined gradually. First, a t-test is performed in each case to determine whether constant terms should be included at all. Second, a likelihood-ratio test is performed to determine whether a trend deterministic component is to be included in each model. For the event-level systems, in the VAR and VECM on levels used in the Johansen procedure, a constant intercept is included, while for the fitted VECM on the differenced data, no intercept is used. In the pooled VAR, a level intercept is included and trends are excluded.

4.4 Johansen's Procedure for Cointegration

Because all event-level series are treated as $I(1)$, cointegration testing is performed for this dataset. This follows the maximum-likelihood approach of Johansen and Juselius (1990) and

Johansen (1991) for Gaussian VARs, explained below. The idea is to transform the VAR estimated by this point (see the methodological sequence in Section 4.1) into the equivalent VECM form, where the cointegration rank r is tested. For the underlying mathematics of this step, see Equations 13 and 14.

Let R_0 be the residuals from regressing ΔY_t on $\Delta Y_{t-1}, \dots, \Delta Y_{t-p+1}$ and D_t , and R_1 the residuals from regressing Y_{t-1} on the same set. The main idea is that in this case, the short-run lags and deterministic terms have been stripped out, and the long-term dynamics can be examined. Define the sample covariance matrices

$$S_{00} = T^{-1}R_0'R_0, \quad S_{11} = T^{-1}R_1'R_1, \quad S_{01} = T^{-1}R_0'R_1, \quad S_{10} = S_{01}' \quad (15)$$

Cointegration rank testing then reduces to the eigenvalue problem

$$S_{10}S_{00}^{-1}S_{01}v = \lambda S_{11}v \quad (16)$$

Where the ordered eigenvalues $\hat{\lambda}_1 \geq \dots \geq \hat{\lambda}_K \in [0, 1)$ are obtained.

The maximum-eigenvalue statistic $\Lambda_{\max}(r_0) = -T \ln(1 - \hat{\lambda}_{r_0+1})$ is then used to test

$$H_0 : \text{rank}(\Pi) = r_0 \quad (17)$$

$$H_A : \text{rank}(\Pi) = r_0 + 1 \quad (18)$$

Sequential testing then proceeds from $r_0 = 0$ until the first non-rejection. Then the last rejecting cointegration rank \hat{r} is obtained. Empirically, every event consistently indicates $\hat{r} \geq 1$, meaning cointegration is present for the data in every event window.

The \hat{r} largest eigenvalues' $\hat{\lambda}_1, \dots, \hat{\lambda}_{\hat{r}}$ associated eigenvectors are then normalised to form $\hat{\beta}$. This lets the error-correction terms be defined:

$$ECT_t = \hat{\beta}'Y_t \quad (19)$$

which are used in the VECM to control for long-run information when modelling in differences.

4.5 Event-level Data: VECM

With rank \hat{r} and error correction terms determined, a VECM is used to model event-level data in first differences ΔY_t :

$$\Delta Y_t = \alpha ECT_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \Delta Y_{t-i} \quad (20)$$

where $ECT_{t-1} = \hat{\beta}'Y_{t-1}$. The Γ_i in this formula capture short-run lagged effects, which is the focus of studying in the Granger causality test.

4.6 Pooled Data: VAR

For the pooled dataset, stationarity in levels allows direct estimation of a VAR(p):

$$Y_t = c + \sum_{i=1}^p \Phi_i Y_{t-i} + u_t \quad (21)$$

There is no need for error correction as cointegration does not play a role.

4.7 Directional Granger Causality Testing

The null of directional blockwise Granger non-causality is tested in the VECM and VAR equations.

For the event-level dataset, the short-run matrices Γ_i can be partitioned into blocks: $\Gamma_i = \begin{pmatrix} \Gamma_{i,PP} & \Gamma_{i,PZ} \\ \Gamma_{i,ZP} & \Gamma_{i,ZZ} \end{pmatrix}$, where $\Gamma_{i,ZP} \in \mathbb{R}^{n \times m}$ relates lagged Polymarket differences to ZQ differences. The null that Polymarket does not Granger-cause ZQ in the short run is

$$H_0 : \Gamma_{1,ZP} = \dots = \Gamma_{p-1,ZP} = 0 \quad (22)$$

jointly across all lags and equations. The null of the reverse direction is formulated analogously as $\Gamma_{i,PZ} = 0$ for all i . In the pooled VAR, the same logic applies with the lag matrices Φ_i .

Rejection in both cases indicates that other than the information from the lagged values of the target block (and the error correction terms), the other block contains incremental information useful to forecasting the future values of the target block.

4.8 Instantaneous Causality

Mathematically, instantaneous causality is a statement about the innovation terms' covariance (u in Equations 14 and 13).

Analogously to Granger causality testing, partition Σ_u into blocks as $\Sigma_u = \begin{pmatrix} \Sigma_{PP} & \Sigma_{PZ} \\ \Sigma_{ZP} & \Sigma_{ZZ} \end{pmatrix}$. The null of no instantaneous cross-source causality is then

$$H_0 : \Sigma_{PZ} = 0 \quad (\text{equivalently } \Sigma_{ZP} = 0) \quad (23)$$

which is tested jointly. In the multivariate setting this is a set of mn covariances. Rejection here suggests that, even after controlling for lagged dynamics and error correction, there remains co-movement within the same one-minute interval, consistent with common shocks and simultaneous movement in both blocks.

4.9 Rolling-window Granger causality (“which lags which”)

To examine and compare the extent of Granger causality, a rolling-window Granger causality analysis is conducted on both the event-level and pooled datasets. A fixed window length of 1440 minutes (1 day) is slid across the relevant datasets.

In each window, the model is re-estimated (VECM at the event level, VAR in the pooled case) with the same deterministic specification and lag order selection rules, and the two blockwise Granger causality tests (Polymarket \rightarrow ZQ and ZQ \rightarrow Polymarket) are performed. This

produces a time series of test statistics for each direction. For the purposes of this thesis, only the share of windows in which each null is rejected is examined.

4.10 Robustness Checks

Two main robustness checks are performed to analyse whether calendar effects or high-frequency artifacts could drive the main results. Both robustness exercises repeat the full empirical empirical process from data-alignment to blockwise Granger causality testing, just as in the main analysis.

The first exercise targets a potential “weekend effect”. Classic evidence for the traditional equity market, such as in French (1980) shows that Monday’s return distribution empirically differs from other trading days, with negative average Monday returns over long samples. In his paper, the author documents this for S&P composite returns for the timeperiod between 1953-1977 and interprets it as a weekend-specific pattern rather than a generic “market closed” effect.

Following this idea, the minute-level dataset is rebuilt by excluding all Monday observations in addition to the removal of Saturdays and Sundays. The objective is to rule out the possibility that Monday-specific return data, in particular for the ZQ dataset, might influence lead-lag patterns between Polymarket and ZQ. Exclusion of Monday data is applied uniformly to both sources before unification, and remaining Tuesday-Friday data is untouched within each event window and in the pooled dataset. The entire methodology is then re-run on the Monday-filtered sample.

The second robustness check addresses frequency sensitivity. Instead of 1-minute fidelity, all timeseries are reaggreated to five-minute bars and the analysis is repeated. The idea is that this reduces potential microstructure noise that can occur at the one-minute horizon from singular trades, while also lowering the number of observations per event.

As an additional robustness diagnostic, all main results and both robustness checks are also re-estimated using Johansen’s trace statistic instead of the maximum eigenvalue method. Here the null and alternative hypothesis differ slightly, with: $H_0 : \text{rank}(\Pi) \leq r_0$ and $H_1 : \text{rank}(\Pi) > r_0$. The new trace statistic is then calculated as:

$$\Lambda_{\text{trace}}(r_0) = -T \sum_{i=r_0+1}^K \ln(1 - \hat{\lambda}_i). \quad (24)$$

and the same “incremental” testing is performed until the cointegration rank \hat{r} is estimated.

5 Results

This section reports the main empirical findings from the pooled the event-level analysis. It highlights patterns in the directional Granger causality tests, the instantaneous causality tests, and the rolling “which-lags-which” tests. Detailed robustness check tables can be found in Appendix B.

5.1 Granger Causality

Table 1: Blockwise Granger causality test PM \rightarrow ZQ

Name	F-statistic	df ₁	df ₂	p-value
Pooled	8.7708	96	3910648	<2e-16 ***
2023 February	0.5908	54	149428	0.9928
2023 March	6.2489	60	238410	<2e-16 ***
2023 May	3.4130	12	172136	<2e-16 ***
2023 June	1.4808	42	213225	0.0230 *
2023 July	0.7328	12	131310	0.7205
2023 September	0.5797	11	112926	0.8471
2023 November	1.2375	9	82726	0.2664
2023 December	0.4273	16	106294	0.9763
2024 January	0.5676	96	213844	0.9998
2024 March	1.6064	30	245890	0.0190 *
2024 May	2.3942	15	114856	0.0018 **
2024 June	1.9469	42	171556	0.0002 ***
2024 July	1.0100	12	200788	0.4361
2024 September	4.5131	48	278940	<2e-16 ***
2024 November	3.8492	345	789528	<2e-16 ***
2024 December	0.7360	240	966889	0.9992
2025 January	0.5480	64	508908	0.9988
2025 March	0.4277	138	467355	1
2025 May	3.4771	27	426084	<2e-16 ***
2025 June	0.8399	120	674600	0.8979
2025 July	1.1158	138	683220	0.1669

The table shows the statistical output for the blockwise Granger causality tests in the direction Polymarket \rightarrow ZQ Futures

Table 2: Blockwise Granger causality test $ZQ \longrightarrow PM$

Name	F-statistic	df ₁	df ₂	p-value
Pooled	7.1393	96	3910648	<2e-16 ***
2023 February	1.0932	54	149428	0.2967
2023 March	5.0076	60	238410	<2e-16 ***
2023 May	4.0590	12	172140	<2e-16 ***
2023 June	1.0953	42	213220	0.3100
2023 July	0.6810	12	131310	0.7715
2023 September	0.1070	11	112926	0.9999
2023 November	5.9940	9	82726	<2e-16 ***
2023 December	0.5485	16	106294	0.9223
2024 January	0.8695	96	213844	0.8154
2024 March	0.0319	30	245890	1
2024 May	1.9907	15	114856	0.0124 *
2024 June	2.2777	42	171556	<2e-16 ***
2024 July	0.6617	12	200788	0.7898
2024 September	26.1722	48	278940	<2e-16 ***
2024 November	8.8129	345	789528	<2e-16 ***
2024 December	0.7939	240	966889	0.9919
2025 January	1.7429	64	508908	0.0002 ***
2025 March	1.7862	138	467355	<2e-16 ***
2025 May	11.2943	27	426084	<2e-16 ***
2025 June	0.8579	120	674600	0.8673
2025 July	2.1178	138	683220	<2e-16 ***

The table shows the statistical output for the blockwise Granger causality tests in the direction ZQ Futures \longrightarrow Polymarket

Tables 1 and 2 show the empirical results for Granger causality tests in each direction, for the event-level, as well as for the pooled dataset.

In the pooled sample, statistically strong predictability is found in both directions. The null that Polymarket (PM) does not Granger-cause ZQ is rejected at conventional significance levels ($F \approx 8.77$, $p < 2 \times 10^{-16}$), and the reverse null that ZQ does not Granger-cause PM is likewise rejected ($F \approx 7.14$, $p < 2 \times 10^{-16}$). This indicates that both series contain significant incremental predictive content for each other in this pooled dataset.

At the level of individual FOMC meetings, the pattern is more heterogeneous. Several meetings show statistically significant $PM \longrightarrow ZQ$ predictability both early on in the dataset, in March, May, and June 2023. For 2024, this is the case for 5 out of 8 markets, in March, May, June, September, and November 2024). For 2025, only the May data shows statistical significance. Similarly, $ZQ \longrightarrow PM$ predictability is significant in a number of meetings, with differences compared to the other direction in June and November 2023, as well as March 2024, January,

March, and May 2025 results. Across meetings, highly significant rejections tend to occur in both directions, but there are also months with asymmetric rejections with Granger causality significant in only one direction. Overall, roughly half of the meetings display at least one direction of significance, with the precise direction varying by meeting. The $ZQ \rightarrow PM$ direction, aka the Polymarket lagging seems to be statistically significant more frequently, than the other way around. This is the case for 11 events, while in the $PM \rightarrow ZQ$ direction this only happens 9 times.

Regarding robustness checks, the results agree for the pooled dataset across all checks. For the event-level dataset, when excluding Mondays, as shown in Appendix B.1.1, the $PM \rightarrow ZQ$ direction does not reject non-causality for the 2024 November event, while the $ZQ \rightarrow PM$ direction rejects for the June 2023 and January 2024 months in addition to the main findings. Considering the robustness check for aggregating data at 5-minute fidelity in Appendix B.1.3, the 2024 May and June events no longer reject non-causality for both directions, for Polymarket-leads-ZQ this is also the case for May 2023. On the other hand, for ZQ-leads-Polymarket robustness, the 2023 February and 2025 June markets reject non-causality. The trace statistics agree with the main maximum-eigenvalue statistic based findings across all datasets and outputs (as shown in Appendix B.2).

5.2 Instantaneous Causality

Table 3: Blockwise Instantaneous causality test

Name	χ^2	df ₁	p-value
Pooled	1466.0978	4	<2e-16 ***
2023 February	0.1067	3	0.9910
2023 March	22.7964	6	0.0009 ***
2023 May	1.7779	3	0.6198
2023 June	7.1283	6	0.3091
2023 July	0.7415	2	0.6902
2023 September	0.3182	1	0.5727
2023 November	3.7030	1	0.0543 .
2023 December	0.0655	1	0.7981
2024 January	2.0396	4	0.7285
2024 March	2185.1144	6	<2e-16 ***
2024 May	4.3906	3	0.2223
2024 June	1.6870	3	0.6398
2024 July	5.3890	3	0.1454
2024 September	80.6587	6	<2e-16 ***
2024 November	32.5638	15	0.0054 **
2024 December	7.1102	10	0.7150
2025 January	11.7129	8	0.1645
2025 March	14.6879	6	0.0228 *
2025 May	14.8822	3	0.0019 **
2025 June	8.0940	6	0.2313
2025 July	27.1094	6	0.0001 ***

The table shows the statistical output for the blockwise instantaneous causality tests. The tests measures contemporaneous comovement, and would therefore be “symmetric” in both directions.

Since instantaneous causality measures contemporaneous co-movement in the blocks, it is symmetric. The results shown in Table 3 show for the pooled test that it is decisively significant with ($\chi^2 \approx 1466$, $df = 4$, $p < 2 \times 10^{-16}$). At the event level, instantaneous causality is significant for a third of all meetings, that is, 7 out of 21, while most meetings do not reject at conventional thresholds.

Regarding robustness checks, the November 2024 event does not reject non-causality when excluding data from Mondays, while aggregating at the 5-minute instead of 1-minute intervals does not reject for March 2024 but does reject for May 2023 and May 2024 in addition to these main results. The pooled dataset’s robustness checks agree with the main findings fully.

Trace statistics once again fully agree with the main methodology’s findings, and the robustness checks’ findings.

5.3 Which lags which

Table 4: Blockwise Granger causality which-lags-which findings

Name	PM \rightarrow ZQ	ZQ \rightarrow PM
Pooled	0.4314	0.4575
2023 February	0.4706	0.6118
2023 March	0.5991	0.4340
2023 May	0.3667	0.2444
2023 June	0.3985	0.3443
2023 July	0.0109	0.0929
2023 September	0.2579	0.3415
2023 November	0.1783	0.2868
2023 December	0.0438	0.0438
2024 January	0.2971	0.4377
2024 March	0.1418	0.0982
2024 May	0.2936	0.2752
2024 June	0.4320	0.3850
2024 July	0.1759	0.2556
2024 September	0.1753	0.3299
2024 November	0.3925	0.4677
2024 December	0.3333	0
2025 January	0.1011	0.4494
2025 March	0.2802	0.4258
2025 May	0.3164	0.4369
2025 June	0.8033	0.8525
2025 July	0.2642	0.3396

The table shows results for rolling window blockwise Granger causality tests. Each entry in the table shows the ratio of 1-day windows rejecting Granger non-causality in the direction determined by the column names to all windows of such length.

The rolling “which-lags-which” analysis shown in Table 4 summarises how frequently each market leads the other across moving windows. For the pooled analysis, the reported shares are of similar magnitude for both directions (approximately 0.43 for PM \rightarrow ZQ and 0.46 for ZQ \rightarrow PM). At the meeting level the shares vary widely compared to one-another. When compared in pairs, some meetings show relatively balanced values near the pooled figures, some tilt toward one direction (such as several 2024 and 2025 meetings, which tilt toward ZQ predicting PM), and a few meetings exhibit pronounced asymmetry (for example December 2024, where ZQ is not at all significant in Granger causing PM data). For 13 out of 21 meetings, the ZQ data predicts Polymarket data for a larger share of the total data timeframe. The other way around this holds for 7 meetings out of 21. The overall heterogeneity across meetings suggests that lead-lag patterns heavily depend on the specific meeting.

Overall, the results seem to indicate that for the pooled data, predictive relationships are heavily present in both directions, while the meeting-level outcomes vary quite a bit across meetings.

In the robustness checks, the trace statistics agree with the findings of the maximum-eigenvalue statistic.

6 Discussion

The evidence presented in this thesis shows that both Polymarket and ZQ futures perform meaningful price discovery. In the pooled sample that rolls all FOMC meetings, always examining the nearest one, blockwise Granger causality tests reject in both directions with very small p-values, showing that each set of data contains incremental predictive content for the other beyond its own lags. This can be interpreted as a decisive finding that neither market is a passive follower on average across meetings. It is however, important to mention the limitation of the data-pooling method which was deployed in the creation of this dataset. Since the nearest event is rolled throughout the data, right after each FOMC decision is announced, a new dataset is rolled into. As the plotted per-meeting implied probabilities in Appendix A show, this means that the implied probabilities jump from close to 0/1 (depending on whether an interest rate decision realises at the meeting or not) to a more ambiguous, lower probability, since the next decision is yet still at least 1 month away. Instantaneous causality results further support this finding, showing highly statistically significant contemporaneous shocks, which cannot be explained by lagged variables in either timeseries. Controlling for this effect, while beyond the scope of this thesis, could provide valuable information regarding the robustness of findings for this dataset.

Event-level tests support these findings. For several meetings, Polymarket leads subsequent changes in ZQ’s implied probabilities, and vice versa, while the meetings where neither leads the other is in minority (8 out of 21). This becomes even more pronounced in more recent markets, since June 2024, which have enjoyed higher volumes compared to before. Still, the statistical significance of Granger causality tests is not fully consistent in either direction throughout time, which indicates that the lead-lag relationship examined in the thesis is more meeting-dependent than the inference on the pooled seems to indicate.

Rolling “which-lags-which” shares count rejections of non-causality, and summarise how frequently each market leads the other within moving one-day windows. In the pooled data, those shares are roughly balanced (about 0.43 for PM \rightarrow ZQ and 0.46 for ZQ \rightarrow PM), while at the meeting level they disperse widely, including cases of extreme asymmetry such as December 2024 where ZQ never leads Polymarket data statistically significantly. The magnitudes of the findings for this analysis also vary widely, further supporting the heterogeneity in results found previously.

Instantaneous causality is large in the aggregate and present in about a third of meetings. As mentioned before, the pooled instantaneous test strongly rejects the null of no contemporaneous covariance, and several meetings show the same, implying that in these cases, implied probabilities tend to adjust essentially simultaneously across both sources rather than participants of one of the two markets implementing information before the other.

From a microstructural perspective, it is important to consider traders’ positions. FOMC meeting information is concentrated and released in a well-established manner (at 14:00 New York time, on the 2nd meeting day). Statement texts such as the Summary of Economic Projections (SEP) are standardised, enabling market participants’ use of algorithmic tools, benefitting primarily the institutional investor-heavy futures markets. However, when information is diffuse and accumulates outside exchange hours, Polymarket’s 24/7 availability lets its traders re-price earlier. The data show both cases: March 2024 can be interpreted as a clear example of Polymarket informationally outperforming, while January and July 2025 are instance of the opposite. Again, neither is consistent.

While results are generally robust for all findings, it is interesting to remark that in cases of disagreements with robustness checks, the futures market data seemed to be more conservative towards rejection of non-causality vis-a-vis Polymarket data at the selected 1-minute frequency than the other way around. Combined with the higher number of statistically significant cases of

causality, and higher count of significant windows in the which-lags-which analysis, this indicates that the futures markets are overall slightly faster at information aggregation and price discovery compared to prediction markets, as exemplified by Polymarket.

Main takeaways can be summarised into three main points. First, there is no single, consistent “informational leader” across the sample. This is evident in the event-level Granger causality tests and in the rolling which-lags-which tests, albeit with a slight advantage to the futures markets. Second, the evidence of predictability in both directions shows that both types of markets contribute to price discovery on average, consistent with semi-strong market efficiency in which common shocks often are absorbed at the same time, and lagged price-adjustment in one market is often quickly followed in the other. Third, these inferences are robust to removing Mondays, to re-sampling at five minutes, and to cointegration rank selection methodology. This reduces concerns that weekend effects, market microstructural noise, or cointegration diagnostics irregularities drive the findings.

As for the research question: How much price discovery takes place on Polymarket and whether it is efficient? The evidence indicates that Polymarket’s price discovery mechanism is not trivial. It incorporates new information as quickly as the futures market in many instances and earlier in some, while in others it swiftly learns from them. This shows that modern prediction markets can be efficient and timely aggregators of information, keeping up with, and occasionally leading traditional financial markets, albeit inconsistently, pointing at some remaining structural inefficiencies.

7 Conclusion

This thesis investigates price discovery and information aggregation behaviour observed on the contemporary prediction market Polymarket. It does so by examining a series of prediction markets on the interest rate decision of the Federal Reserve’s Federal Open Market Committee, interpreting Polymarket’s prices as risk-neutral probabilities, and comparing them to risk-neutral probabilities extracted from 30-Day Federal Funds futures through the CME’s FedWatch tool. A VAR/VECM framework is deployed with directional Granger and instantaneous causality testing on both pooled and meeting-by-meeting data to analyse whether prediction markets or traditional financial markets move first when news regarding upcoming changes to interest rate policy arrive.

The research shows both sources are rather efficient when it comes to price discovery. In pooled analyses, predictive power is highly significant in both directions, and contemporaneous dependence is strong, indicating that information often arrives and is absorbed nearly simultaneously. At the meeting level, the evidence is mixed. Findings from some FOMC meetings show Polymarket leading price discovery, others show futures data leading. The overall picture indicates equal importance rather than complete superiority of either source. Robustness checks show slightly more reliable futures data, while findings for Polymarket are also affirmed as statistically valid and robust.

Limitations of this work are important for considering future research on this topic. The scope is limited to a single prediction market platform with a shared topic. Further research are to be done in this data-rich field extending to further platforms, event topics, and applications. The analysis conducted in this thesis offers a starting point.

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A ZQ and Polymarket implied probabilities

In this section, blue lines display price-implied risk-neutral probabilities of Polymarket assets, while red lines display price-implied risk-neutral probabilities from 30-Day Federal Funds futures.

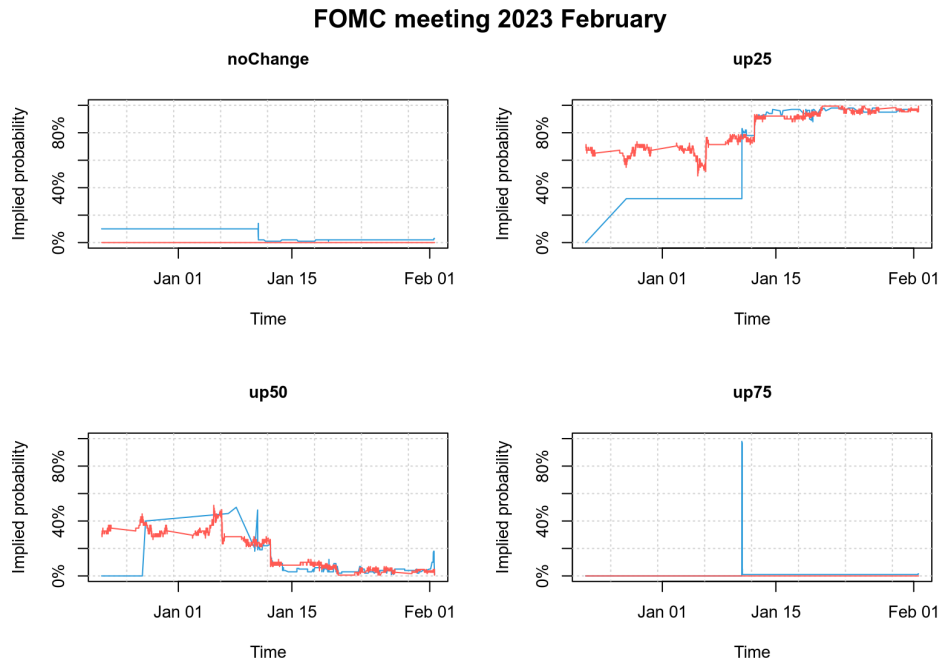


Figure 6: Implied RN Probabilities February 2023 Meeting

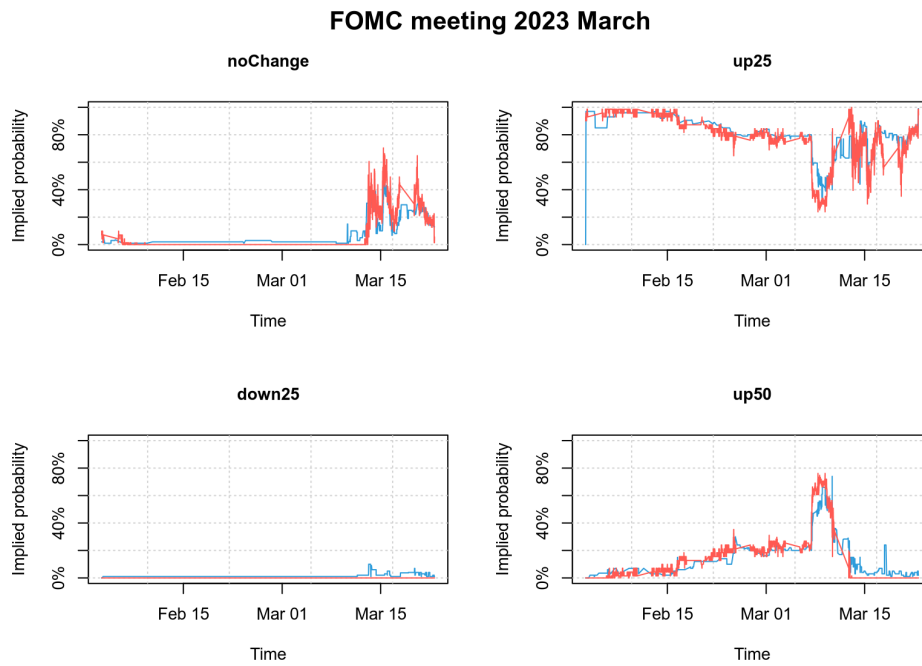


Figure 7: Implied RN Probabilities March 2023 Meeting

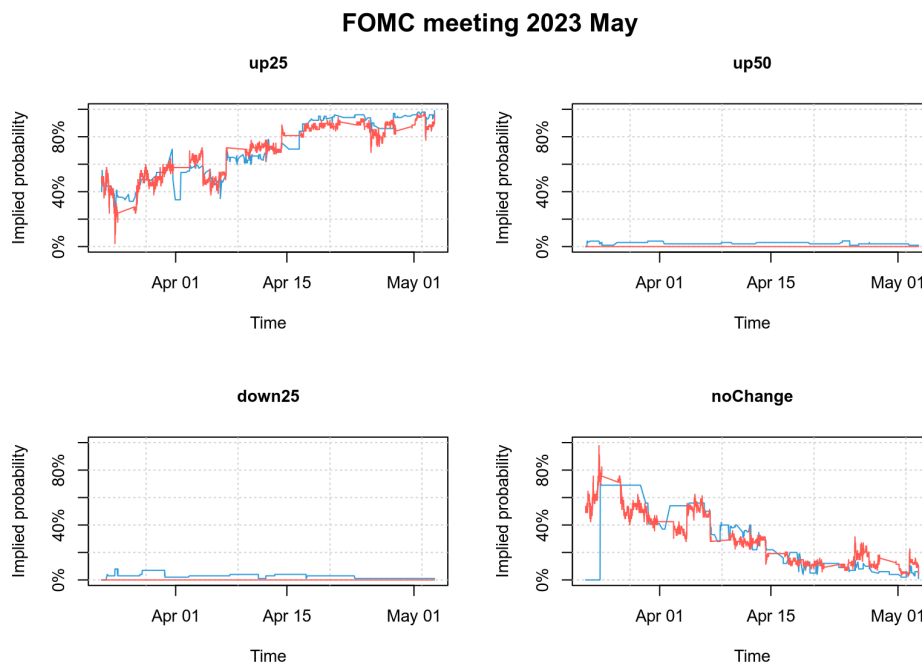


Figure 8: Implied RN Probabilities May 2023 Meeting

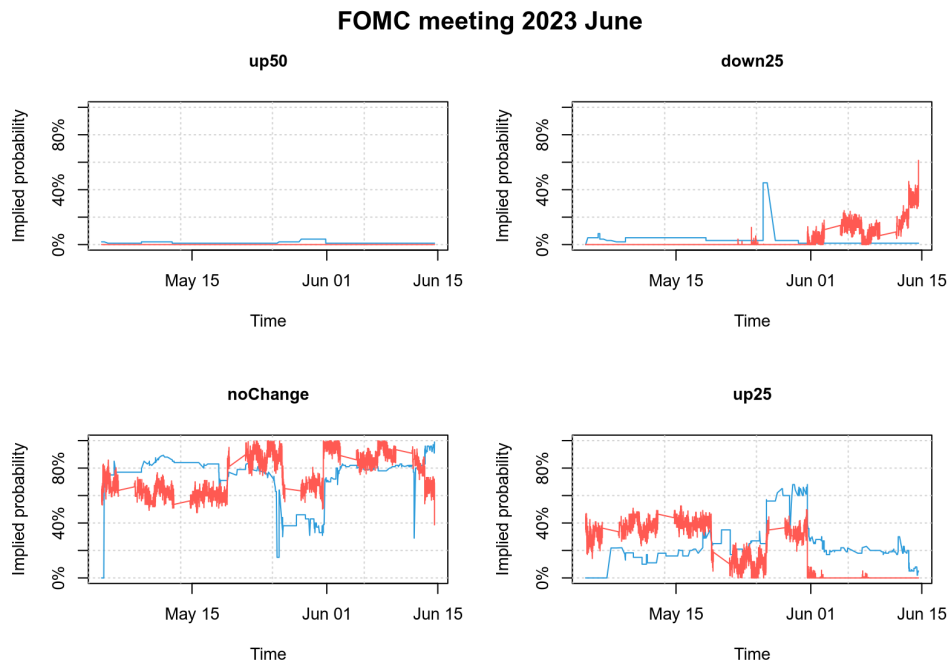


Figure 9: Implied RN Probabilities June 2023 Meeting

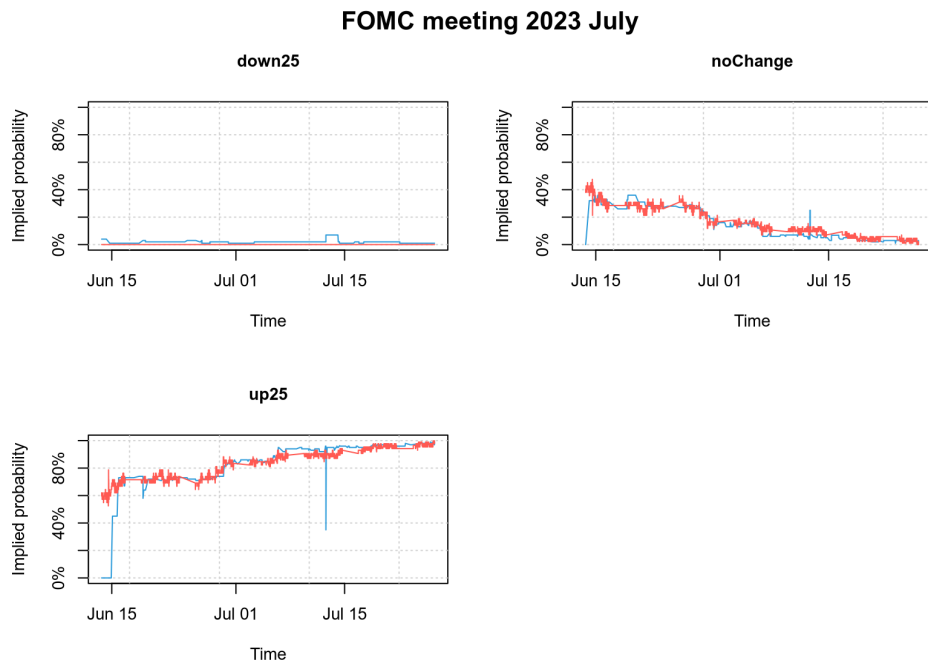


Figure 10: Implied RN Probabilities July 2023 Meeting

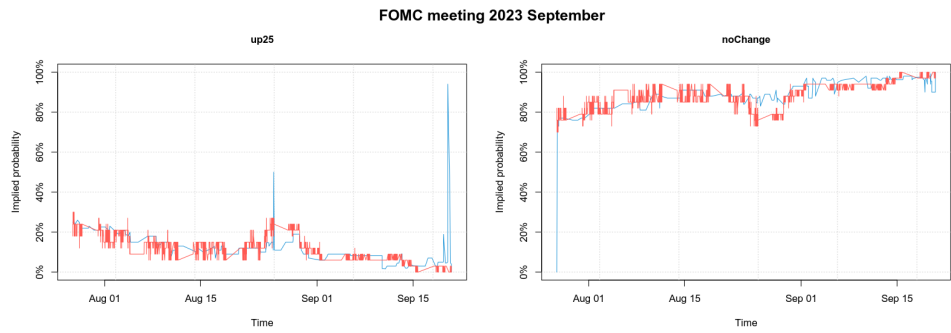


Figure 11: Implied RN Probabilities September 2023 Meeting

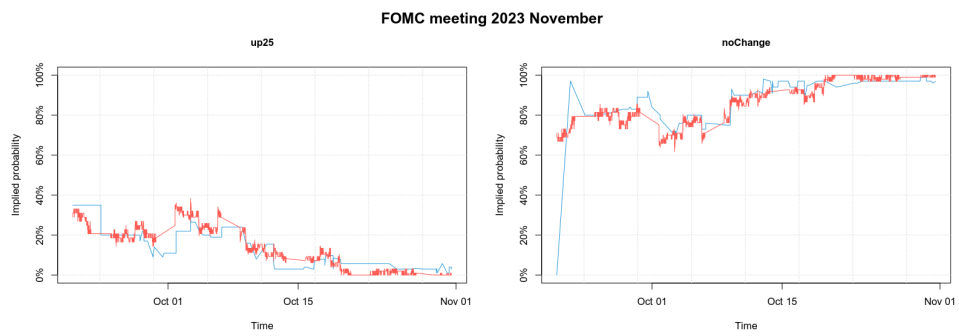


Figure 12: Implied RN Probabilities November 2023 Meeting

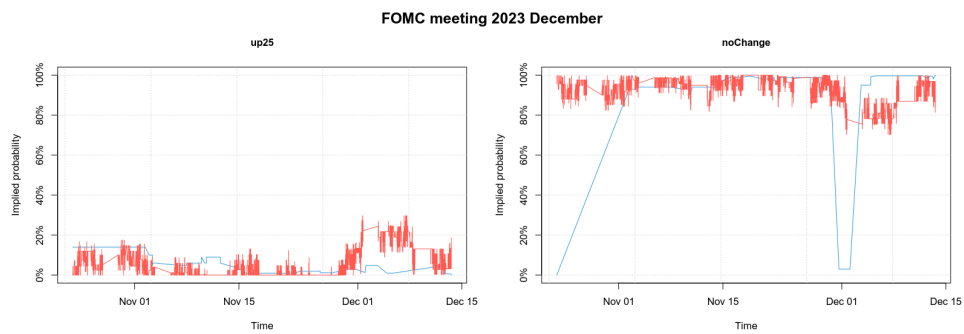


Figure 13: Implied RN Probabilities December 2023 Meeting

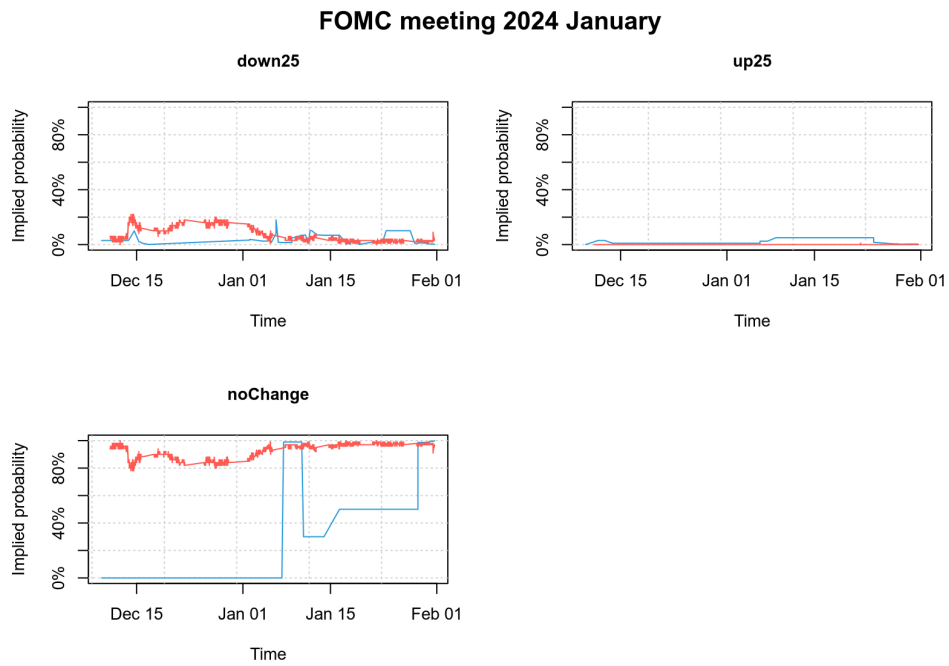


Figure 14: Implied RN Probabilities January 2024 Meeting

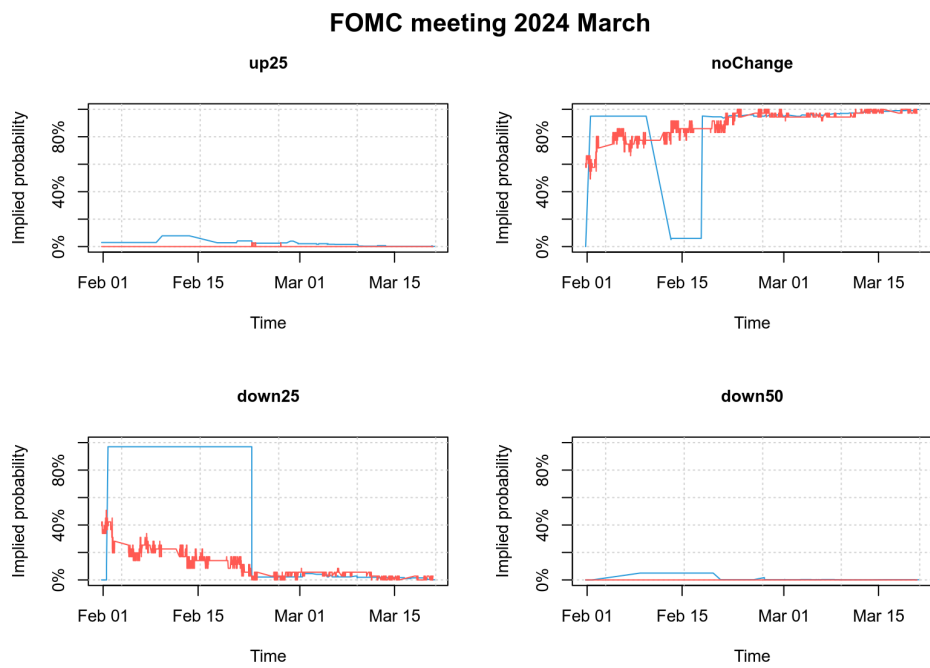


Figure 15: Implied RN Probabilities March 2024 Meeting

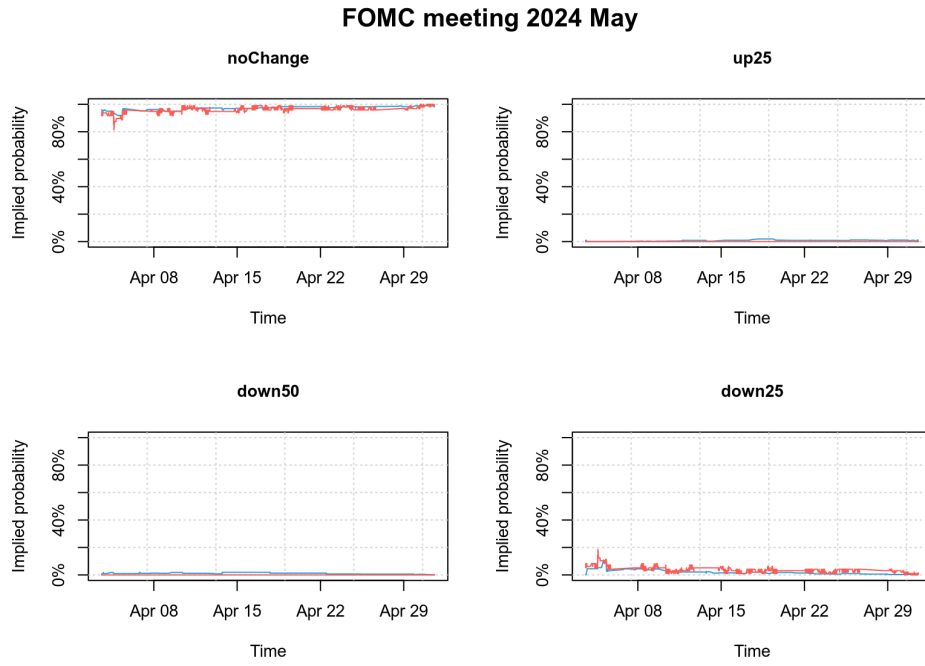


Figure 16: Implied RN Probabilities May 2024 Meeting

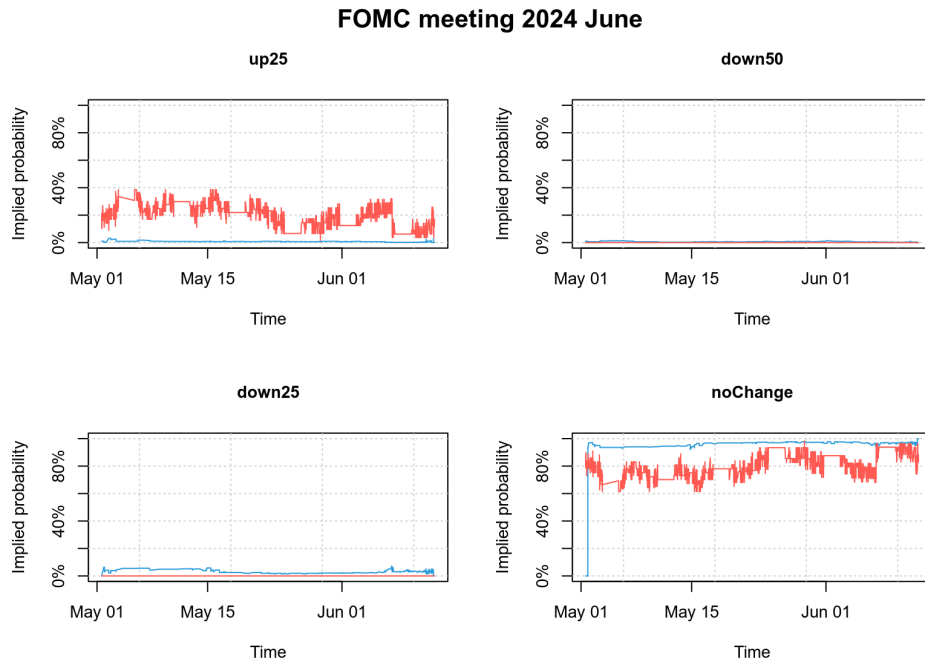


Figure 17: Implied RN Probabilities June 2024 Meeting

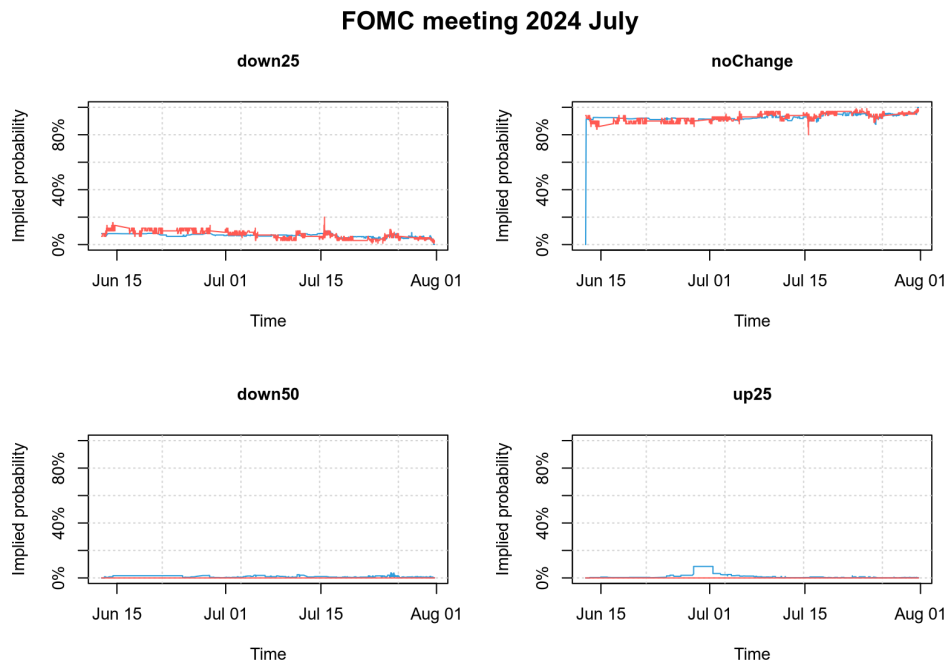


Figure 18: Implied RN Probabilities July 2024 Meeting

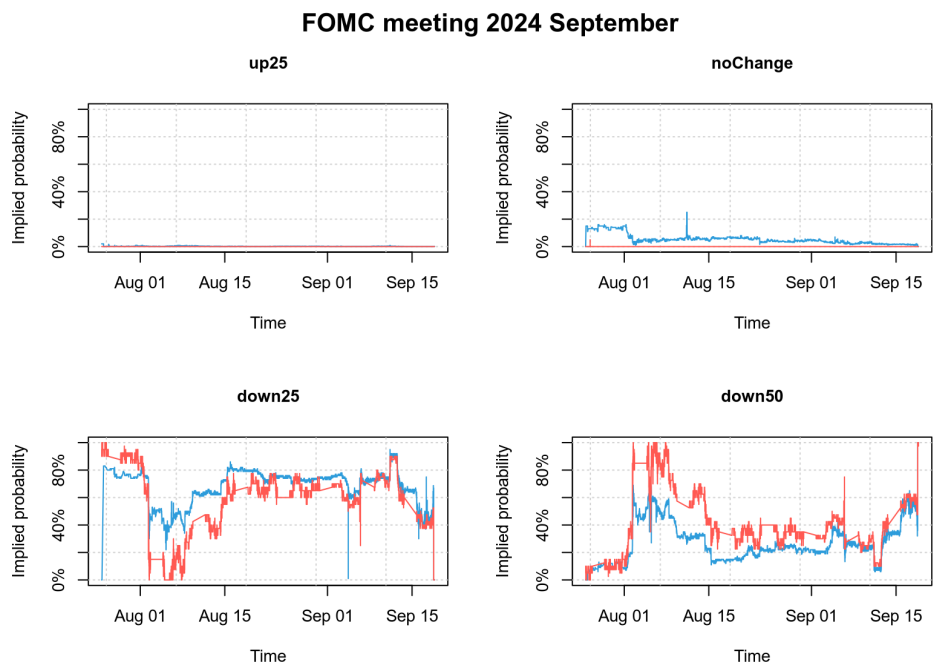


Figure 19: Implied RN Probabilities September 2024 Meeting

FOMC meeting 2024 November

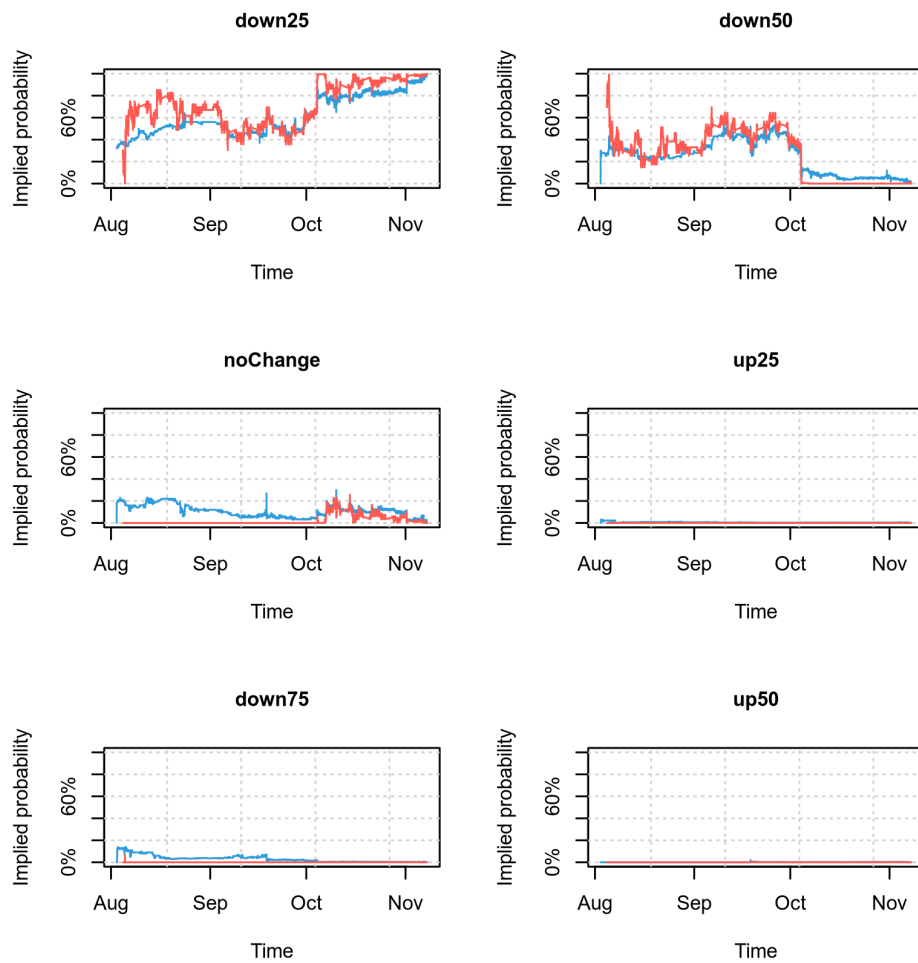


Figure 20: Implied RN Probabilities November 2024 Meeting

FOMC meeting 2024 December

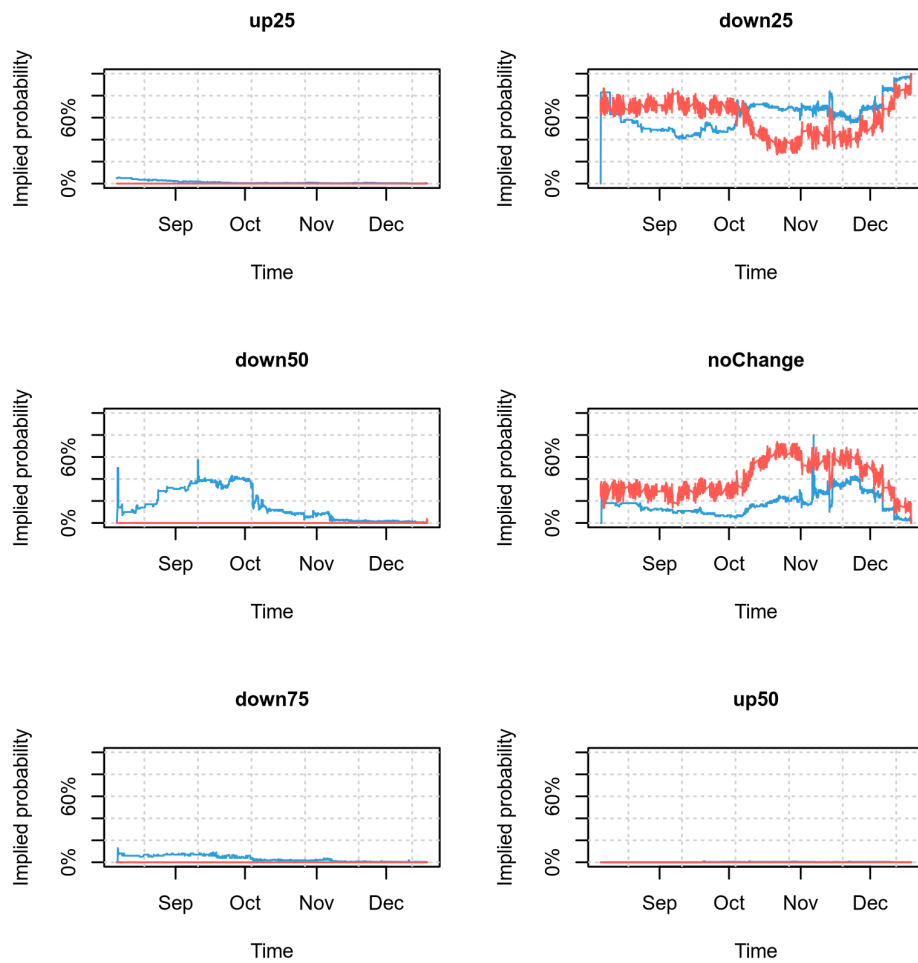


Figure 21: Implied RN Probabilities December 2024 Meeting

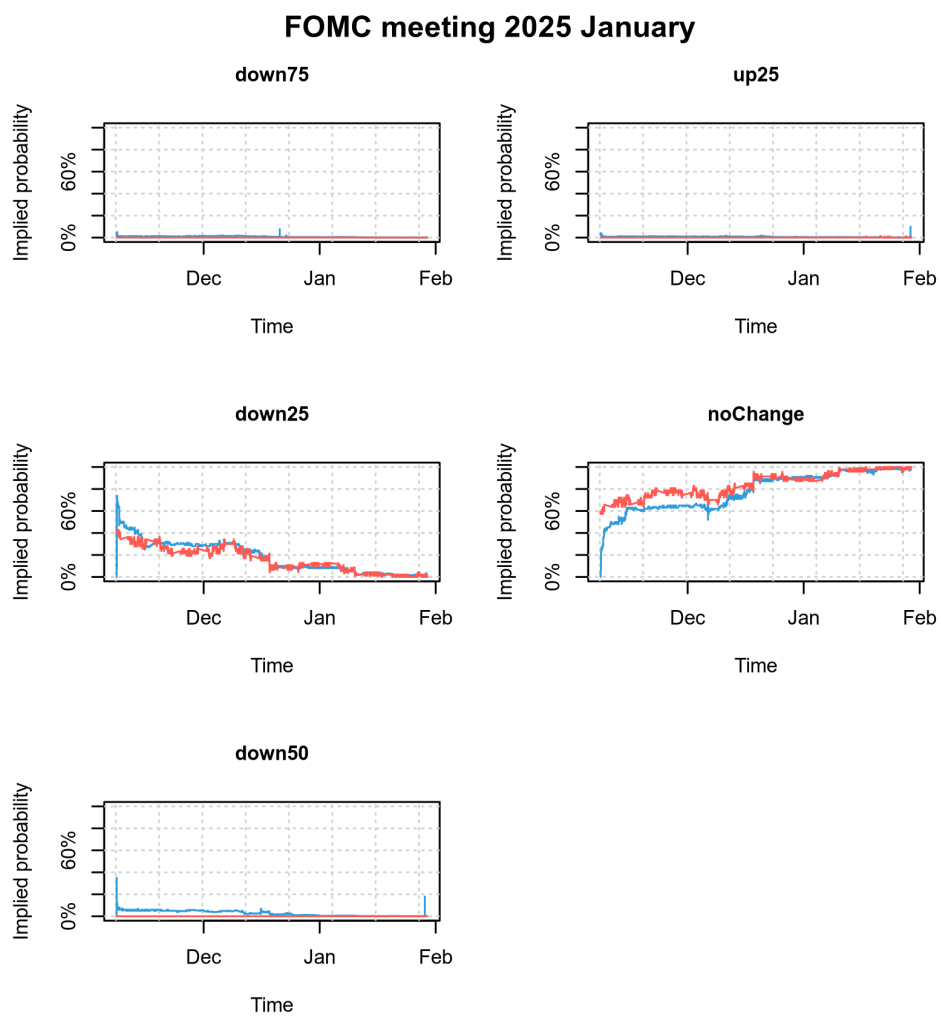


Figure 22: Implied RN Probabilities January 2025 Meeting

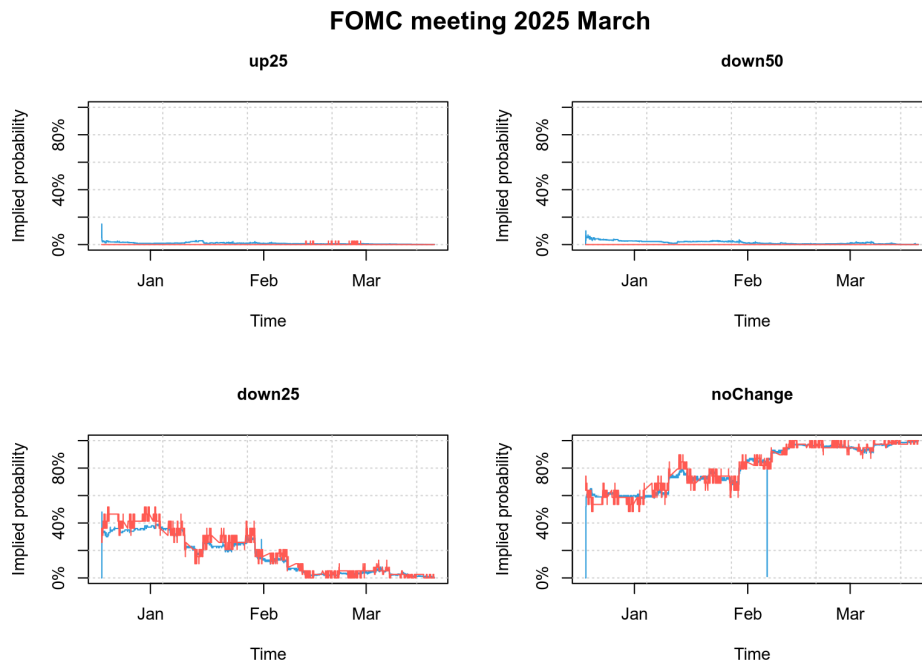


Figure 23: Implied RN Probabilities March 2025 Meeting

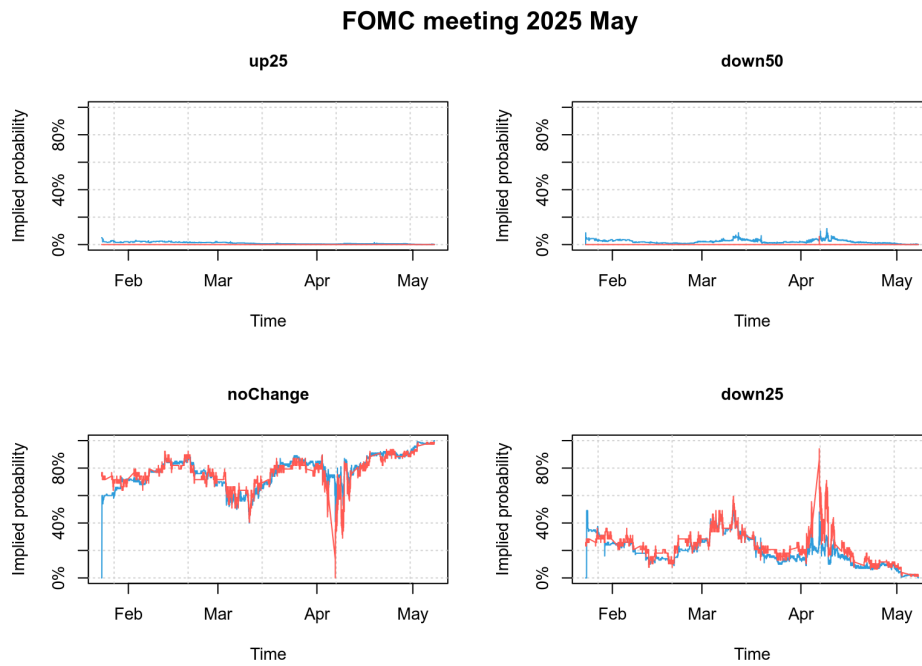


Figure 24: Implied RN Probabilities May 2025 Meeting

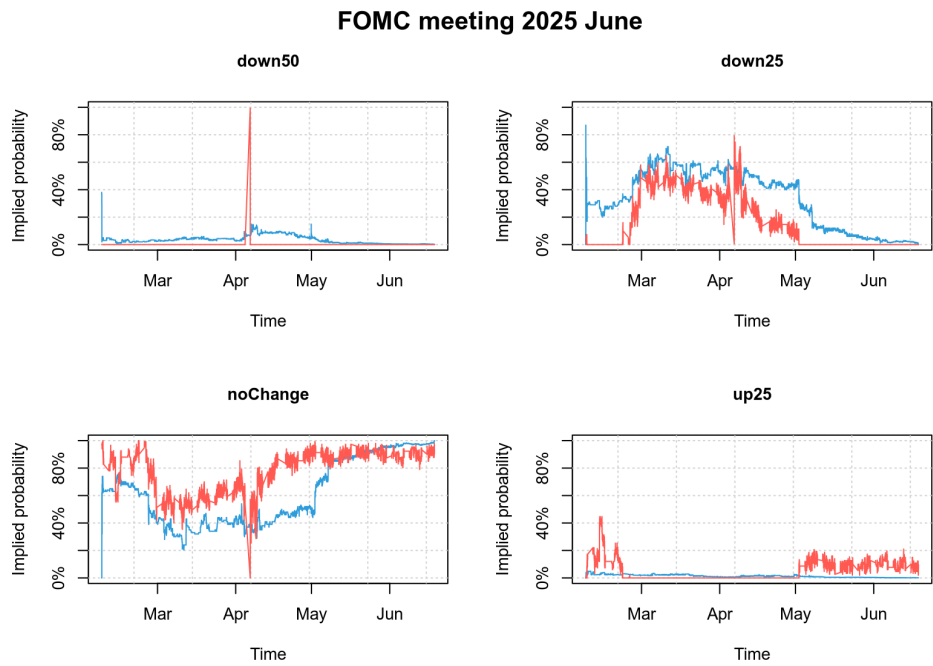


Figure 25: Implied RN Probabilities June 2025 Meeting

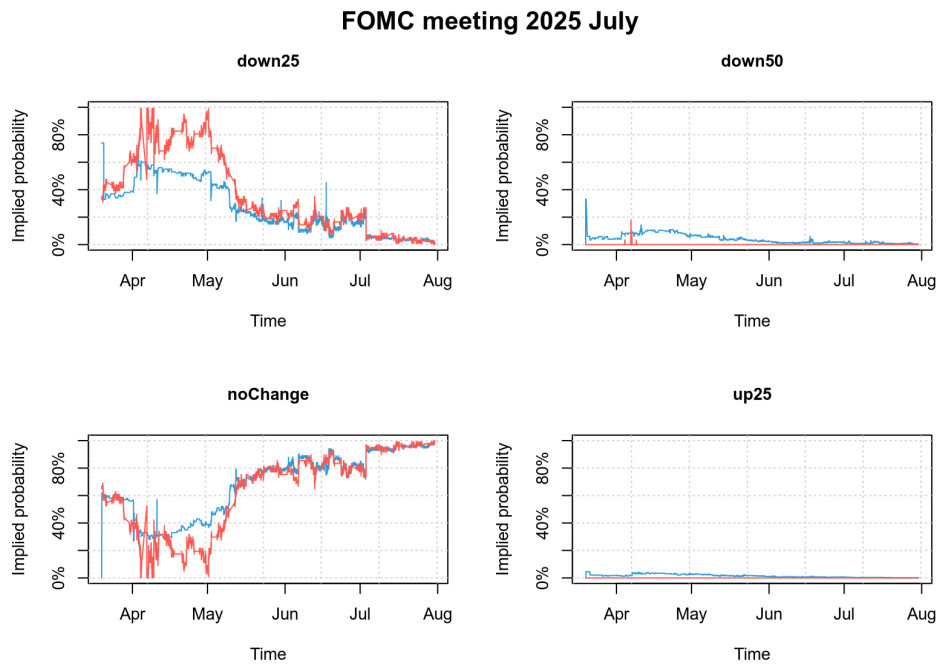


Figure 26: Implied RN Probabilities July 2025 Meeting

B Robustness Check Results

B.1 Maximum-Eigenvalue Test Statistics

B.1.1 Granger Causality: Monday Excluded, 1 Minute Fidelity

Table 5: PM \rightarrow ZQ

Name	F-statistic	df ₁	df ₂	p-value
Pooled	8.1396	96.0000	3127288.0000	0.0000 ***
2023 February	0.5710	54	149428	0.9953
2023 March	3.7700	102	238165	<2e-16 ***
2023 May	3.9537	12	172144	<2e-16 ***
2023 June	1.6036	42	213230	0.0078 **
2023 July	0.8675	12	131310	0.5801
2023 September	0.6167	11	112926	0.8163
2023 November	1.1680	9	82726	0.3107
2023 December	0.6008	11	83978	0.8298
2024 January	0.8476	96	208000	0.8568
2024 March	1.6163	30	245890	0.0177 *
2024 May	3.9536	15	114856	<2e-16 ***
2024 June	2.0103	51	171484	<2e-16 ***
2024 July	1.5163	12	200792	0.1099
2024 September	2.4271	48	278940	<2e-16 ***
2024 November	0.9470	345	789528	0.7526
2024 December	0.7664	240	966889	0.9971
2025 January	0.6234	64	508908	0.9922
2025 March	0.4728	138	467350	1
2025 May	2.9622	30	426060	<2e-16 ***
2025 June	0.6764	120	674600	0.9974
2025 July	1.0137	138	683220	0.4390

Table 6: $ZQ \rightarrow PM$

Name	F-statistic	df ₁	df ₂	p-value
Pooled	6.2858	96.0000	3127288.0000	0.0000 ***
2023 February	1.0631	54	149428	0.3500
2023 March	5.8984	102	238165	<2e-16 ***
2023 May	3.8476	12	172140	<2e-16 ***
2023 June	1.4810	42	213225	0.0230 *
2023 July	0.2726	12	131310	0.9933
2023 September	0.0983	11	112926	0.9999
2023 November	4.0869	9	82726	<2e-16 ***
2023 December	0.3540	11	83978	0.9729
2024 January	1.3101	96	208000	0.0224 *
2024 March	0.0377	30	245890	1
2024 May	2.0926	15	114856	0.0078 **
2024 June	2.0157	51	171484	<2e-16 ***
2024 July	0.9545	12	200788	0.4905
2024 September	26.7800	48	278940	<2e-16 ***
2024 November	1.7889	345	789528	<2e-16 ***
2024 December	0.7395	240	966889	0.9991
2025 January	1.9600	64	508908	<2e-16 ***
2025 March	1.8207	138	467350	<2e-16 ***
2025 May	8.4582	30	426060	<2e-16 ***
2025 June	0.7486	120	674600	0.9819
2025 July	1.6837	138	683220	<2e-16 ***

B.1.2 Instantaneous Causality: Monday Excluded, 1 Minute Fidelity

Table 7: Symmetric

Name	χ^2	df ₁	p-value
Pooled	1447.7516	4.0000	0.0000 ***
2023 February	0.0980	3	0.9921
2023 March	9.2027	6	0.1625
2023 May	6.8323	3	0.0774 .
2023 June	11.4023	6	0.0767 .
2023 July	0.6469	2	0.7236
2023 September	0.0753	1	0.7838
2023 November	1.7168	1	0.1901
2023 December	0.0975	1	0.7548
2024 January	1.7713	4	0.7777
2024 March	2185.5618	6	<2e-16 ***
2024 May	4.4102	3	0.2204
2024 June	1.7426	3	0.6275
2024 July	6.1281	3	0.1055
2024 September	49.0017	6	<2e-16 ***
2024 November	22.1030	15	0.1051
2024 December	8.7837	10	0.5528
2025 January	14.2537	8	0.0754 .
2025 March	12.0977	6	0.0598 .
2025 May	16.8586	3	0.0008 ***
2025 June	5.0376	6	0.5390
2025 July	18.7387	6	0.0046 **

B.1.3 Granger Causality: 5 Minute Fidelity

Table 8: PM \rightarrow ZQ

Name	F-statistic	df ₁	df ₂	p-value
Pooled	11.8903	60.0000	781924.0000	0.0000 ***
2023 February	0.5227	57	29504	0.9989
2023 March	3.7790	36	47525	<2e-16 ***
2023 May	1.9022	3	34408	0.1268
2023 June	1.6130	24	42550	0.0293 *
2023 July	0.8453	28	26067	0.6989
2023 September	0.8772	6	22550	0.5105
2023 November	0.5125	4	16526	0.7266
2023 December	0.2498	7	21222	0.9724
2024 January	0.4095	60	42516	1
2024 March	2.6396	6	49165	0.0147 *
2024 May	1.0792	3	22964	0.3564
2024 June	1.8713	9	34288	0.0513 .
2024 July	0.6703	9	40096	0.7367
2024 September	6.5463	30	55650	<2e-16 ***
2024 November	19.9267	120	157592	<2e-16 ***
2024 December	0.8360	230	192213	0.9666
2025 January	1.1496	152	100896	0.1001
2025 March	0.5386	36	93395	0.9892
2025 May	2.8935	12	85152	0.0005 ***
2025 June	0.7807	36	134830	0.8235
2025 July	1.4535	24	136645	0.0702 .

Table 9: $ZQ \rightarrow PM$

Name	F-statistic	df ₁	df ₂	p-value
Pooled	6.9222	60.0000	781924.0000	0.0000 ***
2023 February	2.3758	57	29504	<2e-16 ***
2023 March	13.7034	36	47525	<2e-16 ***
2023 May	8.0680	3	34412	<2e-16 ***
2023 June	1.3541	24	42545	0.1152
2023 July	0.9026	28	26067	0.6129
2023 September	0.6097	6	22550	0.7228
2023 November	10.2282	4	16526	<2e-16 ***
2023 December	0.4426	7	21222	0.8758
2024 January	1.0231	60	42516	0.4262
2024 March	0.2031	6	49165	0.9759
2024 May	2.2543	3	22964	0.0799 .
2024 June	0.8836	9	34288	0.5390
2024 July	0.6335	9	40096	0.7694
2024 September	25.5765	30	55650	<2e-16 ***
2024 November	8.7257	120	157592	<2e-16 ***
2024 December	0.9037	230	192213	0.8499
2025 January	1.4549	152	100896	0.0002 ***
2025 March	2.1889	36	93395	<2e-16 ***
2025 May	15.6296	12	85152	<2e-16 ***
2025 June	1.7505	36	134830	0.0035 **
2025 July	3.7962	24	136645	<2e-16 ***

B.1.4 Instantaneous Causality: 5 Minute Fidelity

Table 10: PM \longrightarrow ZQ

Name	χ^2	df ₁	p-value
Pooled	842.4022	4.0000	0.0000 ***
2023 February	5.5435	3	0.1361
2023 March	25.3782	6	0.0003 ***
2023 May	9.0238	3	0.0290 *
2023 June	7.8675	6	0.2480
2023 July	4.5078	2	0.1050
2023 September	0.1315	1	0.7169
2023 November	0.2012	1	0.6538
2023 December	0.1005	1	0.7512
2024 January	2.2068	4	0.6978
2024 March	540.7892	6	<2e-16 ***
2024 May	13.7982	3	0.0032 **
2024 June	18.0257	3	0.0004 ***
2024 July	2.4286	3	0.4883
2024 September	141.9033	6	<2e-16 ***
2024 November	55.5491	15	<2e-16 ***
2024 December	15.5152	10	0.1144
2025 January	19.7173	8	0.0115 *
2025 March	12.5042	6	0.0516 .
2025 May	106.7098	3	<2e-16 ***
2025 June	3.4468	6	0.7510
2025 July	15.8769	6	0.0144 *

B.2 Trace Method Test Statistics

B.2.1 Granger Causality: 1 Minute Fidelity

Table 11: PM \rightarrow ZQ

Name	F-statistic	df ₁	df ₂	p-value
Pooled	8.7708	96	3910648	<2e-16 ***
2023 February	0.5908	54	149428	0.9928
2023 March	6.2489	60	238410	<2e-16 ***
2023 May	3.4153	12	172140	<2e-16 ***
2023 June	1.4763	42	213220	0.0239 *
2023 July	0.7328	12	131310	0.7205
2023 September	0.5797	11	112926	0.8471
2023 November	1.2375	9	82726	0.2664
2023 December	0.4273	16	106294	0.9763
2024 January	0.5676	96	213844	0.9998
2024 March	1.6064	30	245890	0.0190 *
2024 May	2.3942	15	114856	0.0018 **
2024 June	1.9469	42	171556	0.0002 ***
2024 July	1.0100	12	200788	0.4361
2024 September	4.5131	48	278940	<2e-16 ***
2024 November	3.8492	345	789528	<2e-16 ***
2024 December	0.7360	240	966889	0.9992
2025 January	0.5480	64	508908	0.9988
2025 March	0.4277	138	467355	1
2025 May	3.4771	27	426084	<2e-16 ***
2025 June	0.8399	120	674600	0.8979
2025 July	1.1158	138	683220	0.1669

Table 12: $ZQ \rightarrow PM$

Name	F-statistic	df ₁	df ₂	p-value
Pooled	7.1393	96	3910648	<2e-16 ***
2023 February	1.0932	54	149428	0.2967
2023 March	5.0076	60	238410	<2e-16 ***
2023 May	4.0588	12	172140	<2e-16 ***
2023 June	1.0690	42	213220	0.3514
2023 July	0.6810	12	131310	0.7715
2023 September	0.1070	11	112926	0.9999
2023 November	5.9940	9	82726	<2e-16 ***
2023 December	0.5485	16	106294	0.9223
2024 January	0.8695	96	213844	0.8154
2024 March	0.0319	30	245890	1
2024 May	1.9907	15	114856	0.0124 *
2024 June	2.2777	42	171556	<2e-16 ***
2024 July	0.6617	12	200788	0.7898
2024 September	26.1722	48	278940	<2e-16 ***
2024 November	8.8129	345	789528	<2e-16 ***
2024 December	0.7939	240	966889	0.9919
2025 January	1.7429	64	508908	0.0002 ***
2025 March	1.7862	138	467355	<2e-16 ***
2025 May	11.2943	27	426084	<2e-16 ***
2025 June	0.8579	120	674600	0.8673
2025 July	2.1178	138	683220	<2e-16 ***

B.2.2 Instantaneous Causality: 1 Minute Fidelity

Table 13: Symmetric

Name	χ^2	df ₁	p-value
Pooled	1466.0978	4	<2e-16 ***
2023 February	0.1067	3	0.9910
2023 March	22.7964	6	0.0009 ***
2023 May	1.7818	3	0.6189
2023 June	7.0150	6	0.3195
2023 July	0.7415	2	0.6902
2023 September	0.3182	1	0.5727
2023 November	3.7030	1	0.0543 .
2023 December	0.0655	1	0.7981
2024 January	2.0396	4	0.7285
2024 March	2185.1144	6	<2e-16 ***
2024 May	4.3906	3	0.2223
2024 June	1.6870	3	0.6398
2024 July	5.3890	3	0.1454
2024 September	80.6587	6	<2e-16 ***
2024 November	32.5638	15	0.0054 **
2024 December	7.1102	10	0.7150
2025 January	11.7129	8	0.1645
2025 March	14.6879	6	0.0228 *
2025 May	14.8822	3	0.0019 **
2025 June	8.0940	6	0.2313
2025 July	27.1094	6	0.0001 ***

B.2.3 Which lags which: 1 Minute Fidelity

Table 14: Which lags which trace findings

Name	PM \rightarrow ZQ	ZQ \rightarrow PM
Pooled	0.4314	0.4575
2023 February	0.4706	0.6118
2023 March	0.5991	0.4340
2023 May	0.3556	0.2556
2023 June	0.3745	0.3904
2023 July	0.0109	0.0929
2023 September	0.2579	0.3415
2023 November	0.1783	0.2868
2023 December	0.0438	0.0438
2024 January	0.2971	0.4377
2024 March	0.1418	0.0982
2024 May	0.2936	0.2752
2024 June	0.4320	0.3850
2024 July	0.1759	0.2495
2024 September	0.1753	0.3299
2024 November	0.3925	0.4677
2024 December	0.3333	0.0000
2025 January	0.1011	0.4494
2025 March	0.2802	0.4258
2025 May	0.3164	0.4369
2025 June	0.8033	0.8525
2025 July	0.2642	0.3396

B.2.4 Granger Causality: Monday Excluded, 1 Minute Fidelity

Table 15: PM \rightarrow ZQ

Name	F-statistic	df ₁	df ₂	p-value
Pooled	8.1396	96.0000	3127288.0000	0.0000 ***
2023 February	0.5710	54	149428	0.9953
2023 March	3.7700	102	238165	<2e-16 ***
2023 May	3.9372	12	172140	<2e-16 ***
2023 June	1.6075	42	213225	0.0075 **
2023 July	0.8675	12	131310	0.5801
2023 September	0.6167	11	112926	0.8163
2023 November	1.1680	9	82726	0.3107
2023 December	0.6008	11	83978	0.8298
2024 January	0.8476	96	208000	0.8568
2024 March	1.6163	30	245890	0.0177 *
2024 May	3.9536	15	114856	<2e-16 ***
2024 June	2.0103	51	171484	<2e-16 ***
2024 July	1.4980	12	200788	0.1164
2024 September	2.4271	48	278940	<2e-16 ***
2024 November	0.9470	345	789528	0.7526
2024 December	0.7664	240	966889	0.9971
2025 January	0.6234	64	508908	0.9922
2025 March	0.4728	138	467350	1
2025 May	2.9622	30	426060	<2e-16 ***
2025 June	0.6764	120	674600	0.9974
2025 July	1.0137	138	683220	0.4390

Table 16: $ZQ \rightarrow PM$

Name	F-statistic	df ₁	df ₂	p-value
Pooled	6.2858	96.0000	3127288.0000	0.0000 ***
2023 February	1.0631	54	149428	0.3500
2023 March	5.8984	102	238165	<2e-16 ***
2023 May	3.8505	12	172140	<2e-16 ***
2023 June	1.4978	42	213225	0.0199 *
2023 July	0.2726	12	131310	0.9933
2023 September	0.0983	11	112926	0.9999
2023 November	4.0869	9	82726	<2e-16 ***
2023 December	0.3540	11	83978	0.9729
2024 January	1.3101	96	208000	0.0224 *
2024 March	0.0377	30	245890	1
2024 May	2.0926	15	114856	0.0078 **
2024 June	2.0157	51	171484	<2e-16 ***
2024 July	0.9473	12	200788	0.4977
2024 September	26.7800	48	278940	<2e-16 ***
2024 November	1.7889	345	789528	<2e-16 ***
2024 December	0.7395	240	966889	0.9991
2025 January	1.9600	64	508908	<2e-16 ***
2025 March	1.8207	138	467350	<2e-16 ***
2025 May	8.4582	30	426060	<2e-16 ***
2025 June	0.7486	120	674600	0.9819
2025 July	1.6837	138	683220	<2e-16 ***

B.2.5 Instantaneous Causality: Monday Excluded, 1 Minute Fidelity

Table 17: ZQ \longrightarrow PM

Name	χ^2	df ₁	p-value
Pooled	1447.7516	4.0000	0.0000 ***
2023 February	0.0980	3	0.9921
2023 March	9.2027	6	0.1625
2023 May	6.7331	3	0.0809 .
2023 June	11.5154	6	0.0737 .
2023 July	0.6469	2	0.7236
2023 September	0.0753	1	0.7838
2023 November	1.7168	1	0.1901
2023 December	0.0975	1	0.7548
2024 January	1.7713	4	0.7777
2024 March	2185.5618	6	<2e-16 ***
2024 May	4.4102	3	0.2204
2024 June	1.7426	3	0.6275
2024 July	6.0461	3	0.1094
2024 September	49.0017	6	<2e-16 ***
2024 November	22.1030	15	0.1051
2024 December	8.7837	10	0.5528
2025 January	14.2537	8	0.0754 .
2025 March	12.0977	6	0.0598 .
2025 May	16.8586	3	0.0008 ***
2025 June	5.0376	6	0.5390
2025 July	18.7387	6	0.0046 **

B.2.6 Granger Causality: 5 Minute Fidelity

Table 18: PM \rightarrow ZQ

Name	F-statistic	df ₁	df ₂	p-value
Pooled	11.8903	60.0000	781924.0000	0.0000 ***
2023 February	0.5227	57	29504	0.9989
2023 March	3.7790	36	47525	<2e-16 ***
2023 May	1.9056	3	34412	0.1263
2023 June	1.6326	24	42545	0.0262 *
2023 July	0.8453	28	26067	0.6989
2023 September	0.8772	6	22550	0.5105
2023 November	0.5125	4	16526	0.7266
2023 December	0.2498	7	21222	0.9724
2024 January	0.4095	60	42516	1
2024 March	2.6396	6	49165	0.0147 *
2024 May	1.0792	3	22964	0.3564
2024 June	1.8713	9	34288	0.0513 .
2024 July	0.6703	9	40096	0.7367
2024 September	6.5463	30	55650	<2e-16 ***
2024 November	19.9267	120	157592	<2e-16 ***
2024 December	0.8360	230	192213	0.9666
2025 January	1.1496	152	100896	0.1001
2025 March	0.5386	36	93395	0.9892
2025 May	2.8935	12	85152	0.0005 ***
2025 June	0.7807	36	134830	0.8235
2025 July	1.4535	24	136645	0.0702 .

Table 19: $ZQ \rightarrow PM$

Name	F-statistic	df ₁	df ₂	p-value
Pooled	6.9222	60.0000	781924.0000	0.0000 ***
2023 February	2.3758	57	29504	<2e-16 ***
2023 March	13.7034	36	47525	<2e-16 ***
2023 May	8.0652	3	34412	<2e-16 ***
2023 June	1.3375	24	42545	0.1246
2023 July	0.9026	28	26067	0.6129
2023 September	0.6097	6	22550	0.7228
2023 November	10.2282	4	16526	<2e-16 ***
2023 December	0.4426	7	21222	0.8758
2024 January	1.0231	60	42516	0.4262
2024 March	0.2031	6	49165	0.9759
2024 May	2.2543	3	22964	0.0799 .
2024 June	0.8836	9	34288	0.5390
2024 July	0.6335	9	40096	0.7694
2024 September	25.5765	30	55650	<2e-16 ***
2024 November	8.7257	120	157592	<2e-16 ***
2024 December	0.9037	230	192213	0.8499
2025 January	1.4549	152	100896	0.0002 ***
2025 March	2.1889	36	93395	<2e-16 ***
2025 May	15.6296	12	85152	<2e-16 ***
2025 June	1.7505	36	134830	0.0035 **
2025 July	3.7962	24	136645	<2e-16 ***

B.2.7 Instantaneous Causality: 5 Minute Fidelity

Table 20: ZQ \longrightarrow PM

Name	χ^2	df ₁	p-value
Pooled	842.4022	4.0000	0.0000 ***
2023 February	5.5435	3	0.1361
2023 March	25.3782	6	0.0003 ***
2023 May	9.0238	3	0.0290 *
2023 June	7.8675	6	0.2480
2023 July	4.5078	2	0.1050
2023 September	0.1315	1	0.7169
2023 November	0.2012	1	0.6538
2023 December	0.1005	1	0.7512
2024 January	2.2068	4	0.6978
2024 March	540.7892	6	<2e-16 ***
2024 May	13.7982	3	0.0032 **
2024 June	18.0257	3	0.0004 ***
2024 July	2.4286	3	0.4883
2024 September	141.9033	6	<2e-16 ***
2024 November	55.5491	15	<2e-16 ***
2024 December	15.5152	10	0.1144
2025 January	19.7173	8	0.0115 *
2025 March	12.5042	6	0.0516 .
2025 May	106.7098	3	<2e-16 ***
2025 June	3.4468	6	0.7510
2025 July	15.8769	6	0.0144 *

C Code

All code used in this thesis and its version history can be viewed at its GitHub repository:
<https://github.com/PeterPavicic/MasterThesis>