The Effects of Monetary Policy on Macroeconomic Expectations: High-Frequency Evidence from Prediction Markets*

Eric T. Swanson
University of California, Irvine
eric.swanson@uci.edu

Renxuan Wang
CEIBS
rxwang@ceibs.edu

Yanbin Wu
University of Florida
yanbin.wu@warrington.ufl.edu

This draft: March 2026

Abstract

When the Federal Reserve raises interest rates, standard macroeconomic models and VARs predict that output, employment, and inflation should fall over the next several quarters. However, monthly-frequency professional macroeconomic forecast revisions are sometimes positively correlated with Fed interest rate changes, leading to a debate about what could explain these puzzling correlations. We bring to bear new high-frequency data on this question from macroeconomic event contracts traded on Kalshi, a CFTC-licensed, U.S.-based event trading exchange and prediction market. These high-frequency event contracts allow us to isolate and estimate the effects of monetary policy and other announcements on Kalshi market-implied macroeconomic expectations. Our results are consistent with standard transmission channels from monetary policy to the macroeconomy, with little or no role for a "Fed Information Effect".

Keywords: *Inflation Expectations, Prediction Market*
JEL Classification: *D22, E43, E52, E58, G14, G18, G23, G24*

*We thank Miguel Acosta, Valentin Haddad, Dun Jia, Benoit Nguyen, Nancy Xu, and participants at the Asian Conference on Macroeconomic Expectations 2025, Columbia Business School Ph.D. Alumni Conference, 2025 World Congress of the Econometric Society, CEIBS Finance and Accounting Symposium, 2025 FIRS Annual Meeting, 2025 European Finance Association Meeting, 2026 AFA Annual Meeting, 2026 Institute for Monetary and Financial Stability Conference, 2026 MFA Annual Meeting, the March 2026 Virtual Seminar on Monetary Ecoomics, and CICF 2026 for helpful discussions, comments, and suggestions.

1. Introduction

When the Federal Reserve raises interest rates, standard macroeconomic models and VARs predict that output, employment, and inflation should fall over the next several quarters (e.g., Christiano, Eichenbaum, and Evans, 2005). It is somewhat surprising, then, that monthly-frequency private-sector professional forecasts of these variables often seem to respond positively to Federal Reserve interest rate surprises. These puzzling results have led to a debate in the literature about what might possibly explain them. On the one hand, the "Fed Information Effect" literature argues that the Fed's monetary policy surprises communicate new information to the private sector about the current state of the economy that the private sector didn't previously have.(see, e.g., Romer and Romer, 2000; Campbell, Evans, Fisher, and Justiniano, 2012; Nakamura and Steinsson, 2018). The idea is that when the Fed raises interest rates, private-sector forecasters infer from that action that the underlying economy must be stronger than they thought. If this Fed Information Effect is strong enough, it can even overcome the standard channel of monetary policy transmission to the economy and lead private-sector forecasters to revise their forecasts in the opposite direction to what standard macroeconomic models would predict.

More recently, however, Bauer and Swanson (2023a) argue that these puzzling regression results are due to the macroeconomic forecast data being available only at a relatively low, monthly frequency. Over the course of an entire month, a great deal of economic news is released to the public beyond just the Fed's monetary policy decision: for example, the U.S. Employment Report, CPI report, auto sales, housing starts, etc. are released every month, and stock market, commodity price, and credit spread data are released continuously throughout each month. Bauer and Swanson (2023a,b) present substantial evidence that this incoming, publicly available news about the economy and financial markets causes *both* the Federal Reserve to change interest rates by more than markets expected *and* macroeconomic forecasters to revise their predictions for macroeconomic variables. For example, when incoming news about the economy is stronger than expected, it tends to be followed both by Federal Reserve monetary policy tightening and by positive private-sector forecast revisions for GDP, employment, and inflation, leading to a positive regression coefficient. Bauer and Swanson refer to this effect as the "Fed Response to News" channel in monthly-frequency forecast regressions.

In this paper, we present new evidence on this debate in the form of macroeconomic forecasts that are available at intradaily frequency from Kalshi, a new, U.S.-based event trading exchange and prediction market that began operating in 2021. In contrast to some smaller-scale, unlicensed predecessors like Intrade and PredictIt, Kalshi has a license from

Figure 1. Kalshi 2022:Q3 GDP Contract Price around June 15, 2022

the U.S. Commodities Futures Trading Commission (CFTC), which allows U.S. financial institutions and investors to participate in the market, permits those participants to take much larger positions (up to $7 million per contract), and lets affiliated companies act as liquidity-providing market makers, all of which enhance market functioning and should improve the accuracy of contract prices for predicting future events.[1] We focus in particular on the most heavily-traded macroeconomic event contracts on the Kalshi exchange: contracts covering the Federal Reserve's federal funds rate announcements and the U.S. CPI, GDP, unemployment rate, and nonfarm payrolls releases.

Because the Kalshi macroeconomic event contracts are traded every day (and typically many times each day), we have access to high-frequency macroeconomic forecast data that was not available to the authors cited above. Rather than running macroeconomic forecast response regressions at monthly frequency, we can run those same regressions at daily frequency and better isolate the effects of monetary policy announcements on the Kalshi market-implied forecasts of macroeconomic variables like CPI inflation, GDP, and unemployment.

Figure 1 provides an example of the Kalshi market response to one such event, the Federal Reserve's 75bp interest rate hike on June 15, 2022, which was the first time the Fed

[1]Polymarket is another recent entrant into the prediction market space and is a close competitor to Kalshi. Throughout our sample, Polymarket did not have a license from the CFTC and thus U.S. financial institutions and investors were blocked from trading on Polymarket's platform. That changed in November 2025, when Polymarket obtained a CFTC license, allowing U.S. investors to participate going forward. We discuss Polymarket and other recent entrants into the event trading space in greater detail below.

had raised the federal funds rate by such a large amount since 1994. The price plotted in the figure is for the contract on whether the next-quarter 2022:Q3 GDP release would be greater than 2.0 percent. Note first that the Kalshi market in this contract is fairly liquid, with multiple trades every day before and after the Fed's announcement. In response to the Fed tightening on June 15, the Kalshi market-implied probability of the Q3 2022 GDP release being above 2 percent fell significantly, from about 50 percent to about 35 percent, suggesting that, on this day, traders viewed the monetary policy tightening as contractionary. This response is consistent with the predictions of standard macroeconomic models and VARs, and inconsistent with the presence of a strong "Fed Information Effect" that would drive private-sector forecasters to revise their forecasts in the opposite direction.

In this paper, we investigate to what extent this finding is true more generally: When the Fed changes monetary policy, how do private-sector market-implied expectations of macroeconomic variables like GDP, unemployment, and inflation react? The high-frequency nature of our Kalshi forecast data allows us to provide new insights into this question.

After surveying the related literature, the remainder of our paper proceeds as follows. In Section 2, we provide the background for the Kalshi market and detailed descriptions of the Kalshi market data. In Section 3, we show that Kalshi contract trading volumes increase substantially around the times of major monetary policy and macroeconomic announcements. In Section 4, we conduct high-frequency regressions of Kalshi market-implied expectations of macroeconomic variables on monetary policy announcements and show that those effects are generally consistent with standard macroeconomic models, with no need for a "Fed Information Effect" to explain the results. We also compare such expectations with alternative decompositions of FOMC shocks. Section 5 provides additional discussion and Section 6 concludes. An Appendix provides details of the construction of the market-implied expectations, summary statistics, and additional results, and an Internet Appendix reports robustness checks.

Related Literature

Our work is related to two major strands of the literature: studies of prediction markets and studies of the Fed Information Effect. Gürkaynak and Wolfers (2005) provide an early survey of prediction markets for macroeconomic data releases in the days before Kalshi and Polymarket. More recently, Diercks, Katz, and Wright (2026) study the liquidity, trading dynamics, accuracy, and distributional properties of the Kalshi market and its market-implied expectations. Consistent with our results below, they find that the Kalshi market provides a useful and accurate high-frequency measure of macroeconomic forecasts.

In contrast to the present paper, they do not study the implications of the Kalshi market responses for the Fed Information Effect and instead focus on a wider range of forecasting and distributional implications. Bürgi, Deng, and Whelan (2026) discuss and model a potential favorite vs. long-shot bias in the Kalshi market data. Eichengreen, Viswanth-Natraj, Wang, and Wang (2026) analyze Polymarket data and study how Polymarket participants' beliefs about the probability of Fed Chair Powell being removed from office is correlated with their expectations of future U.S. monetary policy and macroeconomic outcomes.

For the Fed Information Effect, Sargent and Wallace (1975) and Barro (1976) present early theoretical models in which the central bank may possess superior information about the economy, but Romer and Romer (2000) is the first paper to argue that this effect is empirically important. They find evidence that the Fed had information about future inflation that private sector forecasters did not have, and that the Fed's interest rate changes could be used to infer some of that information. However, Faust, Swanson, and Wright (2004) show that FOMC announcements did not significantly affect private-sector forecasts of the very next macroeconomic data releases (e.g., GDP, retail sales, CPI, etc.), while other macroeconomic data releases such as the employment report, did. They conclude that there is little evidence of a Fed Information Effect in the data. They also show that the Romer and Romer (2000) results for inflation were due to the Volcker disinflation in the early 1980s; excluding that one episode, the Fed's inflation forecasts were no better than those of the private sector.

Campbell, Evans, Fisher, and Justiniano (2012) study how Fed monetary policy announcements affect Blue Chip forecasts of unemployment and inflation. Consistent with Faust et al. (2004) and contrary to Romer and Romer (2000), they find no evidence that Fed announcements contain significant information about inflation. However, they find that monetary policy tightenings are associated with a significant *downward* revision in Blue Chip unemployment rate forecasts, which they attribute to a Fed information effect. Nakamura and Steinsson (2018) find that monetary policy tightenings are associated with a significant *upward* revision in Blue Chip GDP forecasts, and like Campbell et al. (2012), appeal to a Fed Information Effect to explain this puzzle.

However, Bauer and Swanson (2023a) present a variety of evidence against the Fed Information Effect and in support of their alternative "Fed Response to News" explanation. In particular, they show that the Fed's internal Greenbook forecasts are no more accurate than Blue Chip forecasts, that Blue Chip forecasters do not revise their forecasts in response to FOMC announcements in a way consistent with the Fed Information Effect, and that previous authors' results supporting the Fed Information Effect are well explained by an omitted variables bias due to the omission of major macroeconomic data releases and financial market changes from their regressions. Similar to Bauer and Swanson (2023a), we show here that Kalshi market forecasters also do not generally revise their forecasts in the way that the Fed Information Effect literature predicts.

Finally, Jarocinski and Karadi (2020) and Cieslak and Schrimpf (2019) decompose monetary policy surprises into "pure monetary policy" and "information" shocks, depending on whether stock prices move in the opposite direction or same direction as interest rates, respectively. Jarocinski and Karadi (2020) estimate that pure monetary policy shocks are much more important in the U.S. than information shocks (cf. their Figure 1), that pure monetary policy shocks cause future GDP to decline, and information shocks cause future GDP to increase. Cieslak and Schrimpf (2019) find a relatively small role for information shocks in FOMC announcements, but a larger role for those shocks in FOMC minutes releases and speeches by the Fed Chair. Consistent with these studies, we also find at most a small role for information shocks in FOMC announcements, although we find no evidence of an information effect in Fed Chair speeches and at best only slight evidence of an information effect in FOMC minutes releases.

2. Data and Background

Prediction markets have emerged as a powerful mechanism for aggregating dispersed information and forecasting future events. Unlike traditional survey-based forecasts that rely on periodic polling of experts, prediction markets operate continuously and incentivize accuracy through real monetary stakes. Early prediction markets, such as the Iowa Electronic Market and Intrade, demonstrated some success in forecasting some political and economic outcomes, but their scale and liquidity were severely limited by U.S. regulators. The recent approval of prediction market platforms by the U.S. Commodity Futures Trading Commission (CFTC) represents a very significant development, enabling institutional participation, larger position limits, and professional market-making services that enhance price discovery and informativeness. This regulatory advancement has created new opportunities for researchers to study how expectations evolve in real time around important economic events.

Kalshi is a U.S.-based event trading exchange and prediction market that began operating in July 2021. The term "kalshi" is Arabic for "everything" and, consistent with its name, the platform offers event contracts across a wide variety of subjects, including economic data releases, election results, pop culture events, music and film awards, sporting event outcomes, and many others. Unlike previous prediction market alternatives, such as Intrade and PredictIt, Kalshi has obtained regulatory approval from the U.S. CFTC. This allows

U.S. financial institutions to participate on the platform and allows Kalshi to operate on a much larger scale than competing alternatives—for example, traders on Kalshi can take positions of up to $7 million in any one contract, while those on the nonprofit research platform PredictIt are limited to a maximum position of $850.[2] Note that Polymarket, the largest current competitor to Kalshi, did not obtain regulatory approval from the CFTC until November 2025 and, as a result, was forced to exclude all U.S. investors from trading on its platform until that point. In general, U.S. investors' interest in event contracts and prediction markets has been exploding, with several trading platforms recently announcing plans to enter the event contract space.[3]

One of the advantages of having a CFTC license is that U.S. financial institutions can participate on the platform. To enhance liquidity in its markets, Kalshi has an affiliated trading company, Kalshi Trading, which performs market-making services, and there are several other market-making services on the platform as well, including the Susquehanna International Group, one of the largest derivative market-making firms in the world.[4] A long finance literature finds that the presence of market makers on an exchange enhances liquidity, market functioning, and market efficiency (e.g., Grossman and Miller, 1988; Amihud, Mendelson, and Pedersen, 2005; Chordia, Roll, and Subrahmanyam, 2008).

2.1. Event Contracts

Event contracts on Kalshi are generally issued a few months before the corresponding events and typically have a binary outcome: "yes" or "no". Each binary contract is a binary option, offering only two possible payoff outcomes: if the specific yes-or-no event is true at expiration, the buyer receives $1; otherwise, the buyer receives nothing.[5]

For example, a Federal Funds Rate event contract is a binary contract that settles based

[2] See Funt (2022) and the detailed contract specifications for individual contracts at https://www.kalshi.com.

[3] For example, Robinhood has partnered with Kalshi to offer Kalshi contract trading on its platform; Coinbase is in the process of doing the same; CME Group is rolling out its own event contract trading using its FanDuel platform; and Cboe Global Market Inc. and Gemini Space have announced plans to offer event contract trading on their platforms.

[4] See Pound (2022), https://kalshi.com/blog/article/liquid-prediction-markets-are-finally-here, https://www.bloomberg.com/news/articles/2024-04-03/susquehanna-starts-trading-desk-for-event-contracts-on-kalshi, and https://help.kalshi.com/en/articles/13823819-how-to-become-a-market-maker-on-kalshi.

[5] Note that Kalshi offers traders the ability to buy and sell either the "yes" or "no" side of a given outcome. However, buying a "yes" contract and selling a "no" contract are exactly equivalent on Kalshi (and vice versa), because the seller of a contract must post $1 as collateral until the outcome of the contract is resolved at maturity (cf., https://help.kalshi.com/en/articles/13823806-buying-yes-vs-selling-no.) Because of this equivalence, we will use the term "contract" below to refer to the "yes" contract unless explicitly stated otherwise.

on the upper bound of the Federal Reserve's target federal funds rate range after a specified FOMC meeting. The contracts are written as "Will the target federal funds rate be above $[x]$% following the Federal Reserve's meeting on [date t]?", with the underlying based on the numbers published on the Federal Reserve's official website on date t. The contract expires at the end of date t and settles at the end of that same date. Note that for each FOMC date t, there are many such Kalshi contracts, one for each different value of x, spaced 0.25 percentage points apart.

For our analysis, we obtained every trade on Kalshi from July 2021 to December 2025 for the five most heavily traded economic event contracts: the federal funds rate, the Consumer Price Index (CPI), the unemployment rate, nonfarm payrolls, and real Gross Domestic Product (GDP). A summary of these contract specifications is as follows:

- **Federal Funds Rate**: The "Will the target federal funds rate be above [x]%?" contract is summarized above. The underlying instrument is the upper end of the federal funds target range published by the Federal Reserve on its official website on the date specified in the contract.

- **CPI**: The "Will the Consumer Price Index (CPI) increase more than [x]%?" contract corresponds to the percentage change in the value of the Consumer Price Index (CPI). The underlying instrument is the signed one-month percent change in the seasonally adjusted Consumer Price Index for All Urban Consumers (CPI-U) published by the Bureau of Labor Statistics for the month specified in the contract.

- **Unemployment Rate**: The "Will the unemployment rate (U-3) be above [x]%?" contract corresponds to the current U.S. unemployment rate. The underlying instrument is the seasonally adjusted unemployment rate (U-3) reported by the Bureau of Labor Statistics Monthly Employment Situation Report for the month specified in the contract.

- **Nonfarm Payrolls**: The "Will the jobs numbers be above [x]?" contract corresponds to the total nonfarm payroll employment number. The underlying instrument is the change in total nonfarm payroll employment reported by the Bureau of Labor Statistics Monthly Employment Situation Report for the month specified in the contract.

- **GDP**: The "Will real GDP increase by more than [x]%?" contract corresponds to the growth rate of U.S. real GDP. The underlying instrument is the Advance Estimate of the seasonally adjusted percentage change (at an annual rate) in quarterly U.S. real

GDP released by the Bureau of Economic Analysis for the quarter specified in the contract.

Note that all of these contracts expire and are settled at the end of the date on which the corresponding statistics are first released, so future revisions to the data do not affect contract settlement or payouts. Kalshi also often lists other variations of the contracts above that are available for trading—for example, in addition to the above contract for the CPI, investors can purchase binary options for the core CPI (the CPI core contract), the 12-month percentage change in the CPI (the CPI YoY contract), and the 12-month percentage change in the core CPI (the Core CPI YoY contract), among others. For each of the five variables listed above (federal funds rate, CPI, unemployment rate, nonfarm payrolls, and GDP), we focus our analysis on the Kalshi contract that is the most heavily traded over our sample, which is the contract described above.

Also note that for each economic event above and each date, there are multiple binary options contracts traded on Kalshi. For example, for the May 2025 Federal Funds Rate, there ae 11 binary options contracts available, one for each of 11 different strikes: 2.75%, 3%, 3.25%, . . . , 5.25%. (For comparison, the spot federal funds rate in March 2025 was 4.33%.) Of course, the contracts that lie toward the extremes of this strike range are traded much less heavily than those that are closest to being at the money.

2.2. Contract Trading and Liquidity

Traders can buy and sell contracts on Kalshi continuously for 24 hours every day, 7 days each week, except on Thursdays from 3–5am U.S. Eastern Time, when the platform is closed for maintenance.[6]

The Kalshi market for the five economic event contracts described above is generally fairly liquid, with trades every day on average. (Moreover, the market liquidity increases substantially around relevant macroeconomic news announcements, as we show and discuss below.) Table 1 reports summary trading statistics for each of the five event contracts described above. The first three columns of the table report daily trading statistics for each contract, the middle three columns report trading statistics for each contract over its entire history, and the last three columns report trading statistics for each event (e.g., the May 2025 Federal Funds Rate). Recall that, for each event, there are multiple binary options contracts available on Kalshi, so the number of contracts is roughly nine times larger than the number of events.

[6] See https://help.kalshi.com/trading/what-are-trading-hours for more details.

Table 1. Kalshi Contract Trading: Summary Statistics

Summary statistics for trading activity in Federal Fund Rate, CPI, Unemployment Rate, Nonfarm Payrolls, and GDP event contracts on the Kalshi exchange. The first three columns report the number of trades, total trading volume, and total dollar trading volume per contract per trading day; the next three columns report the same statistics at the per-contract level, and the last three columns report the statistics at the per-event level. Sample: July 2021 to December 2025. See text for details.

	Per Contract Per Day			Per Contract			Per Event		
	Trades	Volume	$Volume	Trades	Volume	$Volume	Trades	Volume	$Volume
				Federal Funds Rate					
N	13,924	13,924	13,924	350	350	350	36	36	36
Mean	9.3	3,070.7	1,453.0	371.5	122,161.4	57,805.3	3,612.2	1,187,679.8	561,996.3
s.d.	48.0	12,366.1	6,711.5	1,397.7	330,452.1	160,512.2	5,780.6	1,215,130.2	553,417.4
Min	1	1	0.01	1	1	0.02	23	2,704	2,093.7
P25	1	100	14.1	24	5,365	1,098.4	1,353.5	598,955.5	287,829.8
P50	2	446	122.9	76.5	22,253.5	9,919.7	2,289.5	838,194.5	372,206.2
P75	6	1,691.5	686.5	250	82,209	39,202.0	3,987.5	1,516,953.5	702,795.4
Max	1,973	504,107	315,710.8	19,085	3,745,708	1,928,358.8	35,337	6,725,996	2,951,501.0
				CPI					
N	8,579	8,579	8,579	389	389	389	55	55	55
Mean	9.3	2,007.2	1,091.2	205.3	44,266.6	24,064.4	1,451.8	313,085.9	170,201.0
s.d.	19.0	7,351.1	4,291.5	346.7	101,622.2	56,481.0	1,642.6	492,083.2	273,324.4
Min	1	1	0.02	1	1	0.02	36	2,753	1,223.7
P25	2	89	25.1	21	3,836	1,452.1	321	43,257	23,531.0
P50	4	365	145.5	96	15,401	8,712.9	718	140,406	70,262.4
P75	9	1,327	658.0	244	37,322	19,705.6	1,984	288,105	148,735.4
Max	332	194,179	122,727.4	2,793	785,062	447,133.7	7,040	2,263,062	1,330,679.7
				Unemployment Rate					
N	4,930	4,930	4,930	377	377	377	54	54	54
Mean	9.5	1,534.5	857.9	124.1	20,066.2	11,218.5	866.6	140,091.5	78,322.0
s.d.	21.1	5,604.2	3,499.1	290.1	52,202.8	30,516.4	1,505.3	271,493.3	153,025.3
Min	1	1	0.02	1	5	0.1	41	1,850	976.2
P25	1	40	11.4	8	616	423.9	140	9,777	5,673.5
P50	3	167	73.8	27	2,866	1,750.3	235.5	26,598	15,796.4
P75	8	760	364.6	74	9,627	4,852.3	750	90,851	54,443.6
Max	391	93,371	76,255.3	2,303	421,079	311,666.8	6,451	1,274,148	767,256.7
				Nonfarm Payrolls					
N	4,373	4,373	4,373	252	252	252	34	34	34
Mean	14.3	3,132.3	1,802.7	247.8	54,355.3	31,282.7	1,836.6	402,868.5	231,859.9
s.d.	33.3	10,500.1	6,781.4	531.9	120,920.8	71,556.5	2,583.0	598,322.7	341,583.3
Min	1	1	0.02	1	4	3.9	144	18,531	9,967.6
P25	2	71	21.0	32.5	4,362.5	2,388.1	311	65,990	41,340.8
P50	4	434	174.9	70	15,374	7,759.6	433.5	123,588	62,693.9
P75	12	1,949	974.2	203.5	42,099	23,235.8	2,103	363,590	186,655.5
Max	760	247,187	173,625.5	4,251	946,048	611,968.4	9,683	2,232,242	1,169,374.4
				GDP					
N	5,873	5,873	5,873	146	146	146	18	18	18
Mean	9.9	1,628.5	860.7	397.3	65,507.8	34,621.2	3,222.6	531,341.4	280,816.4
s.d.	20.2	6,244.4	3,535.7	728.5	127,911.4	69,566.6	5,825.7	1,026,722.0	546,800.1
Min	1	1	0.02	1	5	0.7	135	7,271	4,494.8
P25	1	50	16.0	38	3,993	2,198.9	590	61,167	33,230.4
P50	3	240	100.0	109.5	11,198.5	5,623.2	860.5	90,185.5	48,954.0
P75	9	1,059	485.6	404	43,579	22,892.9	1,445	197,240	104,148.1
Max	394	247,907	126,699.2	4,270	745,945	378,244.5	21,048	3,421,765	1,862,898.1

For example, for the Federal Funds Rate contracts, there are 36 events in our sample (36 FOMC meetings from July 2021 to December 2025), and there are on average 3,612 trades per event, with an average volume of 1,187,680 contracts traded, for a dollar value of $561,996, a nontrivial amount. On a per contract per day basis, there are on average 9.3 trades per day, with an average volume of 3,071 contracts traded, for a dollar value of $1,453. Although these daily averages might not seem very large, recall that many contracts toward the extremes of the distribution are not heavily traded, and that all contract trading volumes are relatively thin when the contract is first introduced but ramp up dramatically as the expiration date approaches, as can be seen in Figure 2. The average daily trading statistics in Table 1 are for all contracts on all days.[7]

Trading statistics for the other contracts listed in Table 1 are generally similar to those for the Federal Funds Rate contracts, although the values for the Nonfarm Payrolls and GDP contracts are somewhat smaller. Kalshi only introduced Nonfarm Payrolls event contracts in March 2023, so there is a shorter sample for those contracts. Similarly, the Kalshi GDP event contracts have expirations only once per quarter because the advance estimate of U.S. real GDP is released only once per quarter; as a result, there are fewer events (data releases) over our sample and average trading volumes per contract can be a little lower since trading tends to increase closer to contract expiration.

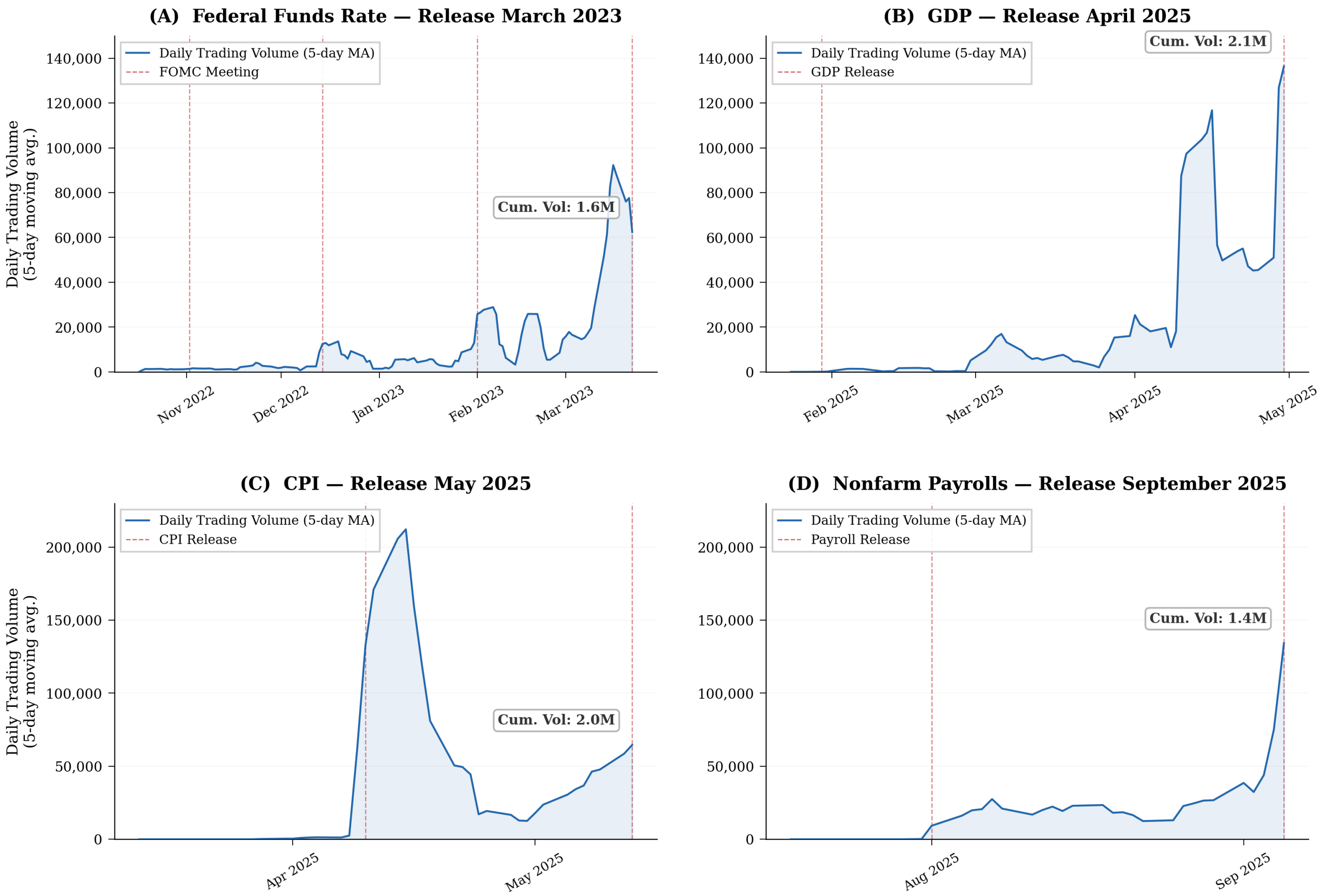
Reflecting their generally high liquidity, bid-ask spreads on these five event contracts are relatively small, typically 1 cent for contracts that are close to being at the money, although contracts toward the extremes of the strike distribution generally have wider bid-ask spreads.

Figure 2 plots the trading volumes for four examples of Kalshi market trading volumes for four different types of events: the Federal Funds Rate contract expiring in March 2023 (Panel A), the GDP contract expiring in April 2025 (Panel B), the CPI contract expiring in May 2025 (Panel C), and the Nonfarm Payrolls contract expiring in September 2025 (Panel D). Each panel plots the 5-day moving average of daily trading volume (summed across all strikes) for a single contract expiration, identified by its release date. The cumulative trading volume for each contract is reported in the inset box in each panel.

There are a few points to take away from Figure 2. First, note that trading volumes are generally large in each of these examples, well over one million total contracts traded in each panel. Second, trading volumes generally increase as the expiration date approaches. Finally, in each panel, a vertical dashed red line denotes the dates of previous releases of

[7]Note that we do not include a contract in our sample on days when there is no trading in that contract. Thus, the minimum values in Table 1 are nonzero.

Figure 2. Trading Volume Patterns across Event Contract Types



Note: Each panel plots the 5-day moving average of daily trading volume (summed across all strikes) for a single contract expiration, identified by its release date. Vertical dashed lines mark relevant macro announcement dates: FOMC meetings (panel A), GDP releases (panel B), CPI releases (panel C), and Nonfarm Payrolls releases (panel D). The cumulative trading volume over the life of each contract is annotated in each panel.

the contracted event (i.e., FOMC announcements in Panel A, GDP releases in Panel B, etc.), and trading volumes typically spike around the times of those releases, as well as other related macroeconomic and monetary policy events, discussed further below.

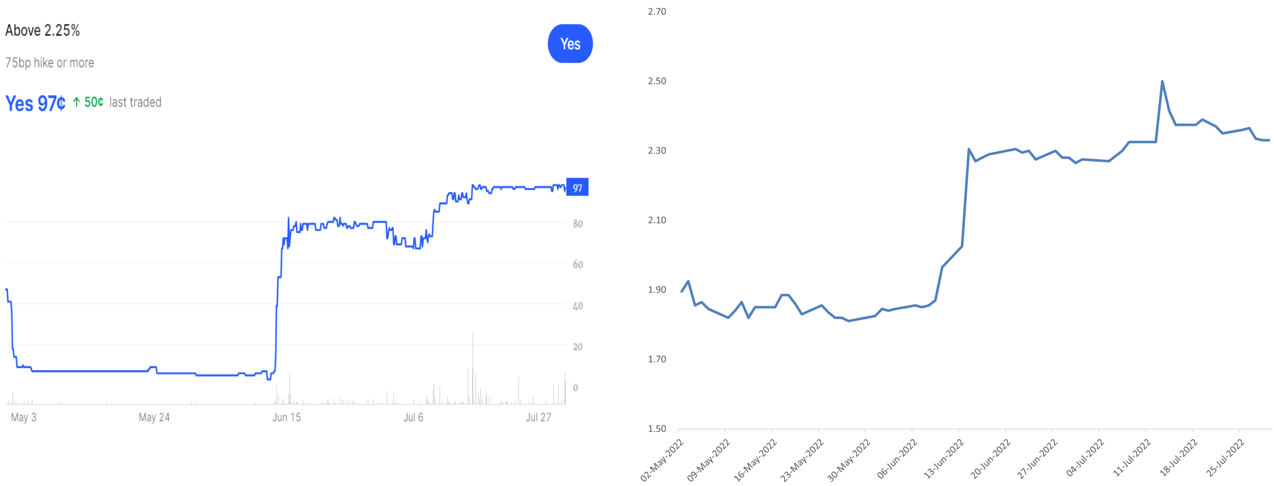
Further evidence of the liquidity of these contracts is provided in Figure 3. The left-hand panel reports the Kalshi market price of the July 2022 Federal Funds Rate above 2.25% contract from May 3, 2022, to its expiration on July 27, 2022. The right-hand panel reports market prices for the corresponding federal funds futures contract from the Chicago Mercantile Exchange over the same period.[8] The Kalshi contract in Figure 3 is

[8]There are two technical points to note in Figure 3: First, federal funds futures contracts settle based on the average daily federal funds rate over the entire contract month. Since the FOMC announcement in this example was on July 27, the right-hand panel of Figure 3 reports fed funds futures rates for the August 2022

Figure 3. Kalshi Federal Funds Rate Contract vs. Federal Funds Futures

(A) Kalshi July 2022 Federal Funds Rate

(B) CME Federal Funds Futures Rate



a binary option while the CME fed funds futures rate is essentially an expected value, but the behavior of the two contracts clearly track each other closely. In May 2022, the upper bound of the Fed's target federal funds rate range was 1%, and markets expected additional Fed tightening at the June 15 and July 27 FOMC meetings, as evidenced by the August CME fed funds futures rate of about 1.8% in the right-hand panel. However, the probability of the fed funds rate being greater than 2.25% by the end of July was relatively low, only about 10% according to the Kalshi contract in the left-hand panel. On June 15, the FOMC raised the federal funds rate target by a greater-than-expected 75 basis points (bp), which led to significant moves on both the CME and Kalshi markets within minutes of the announcement—the August federal funds futures rate increased to about 2.3%, while the Kalshi probability of the rate being above 2.25% rose to about 80%. After June 15, as the July 27 FOMC meeting approached, both the fed funds futures rate and the Kalshi probability drifted upward a bit further.

The example in Figure 3 is a little unusual in terms of the size of the movements in the Kalshi and federal funds futures prices, but the point that Kalshi contracts and federal funds futures co-move closely holds in general throughout our sample. In particular, the five types of Kalshi contracts we study (Federal Funds Rate, CPI, Unemployment Rate, Nonfarm Payrolls, and GDP) are heavily traded and market prices respond quickly to news such as

contract, which fully reflects the federal funds rate that will be announced on July 27 and take effect on July 28. Second, fed funds futures contracts pay $100 - r$ at expiration, where r is the average federal funds rate just mentioned. Thus, the federal funds futures contract price p on date t implies an expected federal funds rate of $r = 100 - p$. The right-hand panel of Figure 3 plots the implied rate r on each date rather than the contract price p.

macroeconomic data releases, as we verify empirically in Section 3, below.

2.3. Kalshi Market-Implied Expectations

In some of our analysis below, we report the Kalshi market-implied expectation of a given macroeconomic event (federal funds rate, CPI release, etc.). The prices of the Kalshi contracts are closely tied to the probabilities of the underlying events, and the contracts are heavily traded, so it's relatively straightforward to construct a daily measure of the market-implied risk-neutral probability distribution for the event—i.e., the probability distribution taking market prices as being risk-neutral.[9] From that probability distribution, we can compute the corresponding market-implied expectation. We summarize how we compute those expectations here, and provide additional technical details in Appendix A.

In particular, let r_h denote the realized value of an event at date h, such as the federal funds rate or CPI release. Let p_{ths} denote the price at time t for an event contract expiring at date h with a strike value of s: that is, the contract pays off \$1 if $r_h > s$ and zero otherwise. For each strike value s, we thus observe

$$cdf_{th}(s) = 1 - p_{ths}, \tag{1}$$

where $cdf_{th}(x)$ denotes the market-implied cumulative distribution function for the realization r_h.

Let s_{thi}, $i = 1, \ldots, K$, denote the set of strikes that are traded at date t for realization r_h, sorted in increasing numerical order, so $s_{thi} < s_{thj}$ for $i < j$. We define the values

$$pdf_{thi} \equiv cdf_{th}(s_{th,i+1}) - cdf_{th}(s_{thi}), \tag{2}$$

for $i = 1, \ldots, K-1$, and $pdf_{th0} \equiv cdf_{th}(s_{th1})$ and $pdf_{thK} \equiv 1 - cdf_{th}(s_{thK})$, which are essentially the Kalshi market-implied probability density function/probability mass function for the corresponding outcome r_h. We also define $s_{th0} \equiv s_{th1} - (s_{th2} - s_{th1})$, and $s_{th,K+1} \equiv s_{thK} + (s_{thK} - s_{th,K-1})$.[10] We then compute the Kalshi market-implied expected value of r_h

[9]We first aggregate the trade-level data into a daily-frequency data set by calculating the last trade of each day. This is the default data set used in our analysis, although we also consider an alternative daily price measure—the volume-weighted average prices using all traded contracts throughout the day—as a robustness check. If a contract does not trade on a given day, we use the previous day's value (this happens mostly for contracts at the lower or upper end of the range of strikes, or for contracts that are far from expiration). For a given event (e.g., August 2024 CPI), we include trading days from the first day on which any contract related to that event has traded; that is, we drop the days before the event's first trade. Note that this implies we include a contract with zero trading on a given day as long as some contract for the same event has traded by that day.

[10]Note that pdf_{th0} and pdf_{thK} are usually very small, so the exact values of s_{th0} and $s_{th,K+1}$ usually do

as

$$E_t[r_h] \equiv \sum_{i=0}^{K} pdf_{thi} \cdot \Big(\frac{s_{thi} + s_{th,i+1}}{2}\Big). \tag{3}$$

Note that contracts at the very low and very high end of the range of strikes are typically much less liquid than contracts near the middle and have larger bid-ask spreads. We found that these extreme contracts sometimes introduced excess volatility into the expectation measure (3), so for our baseline results below we compute the expectation (3) excluding the highest strike and lowest strike.[11]

2.4. Accuracy of Kalshi Market-Implied Expectations

We check the accuracy of our Kalshi market-implied expectations measures by comparing them to survey-based forecasts for macroeconomic variables from the Blue Chip Survey of Forecasters (BC) and the Philadelphia Fed's Survey of Professional Forecasters (SPF) over our sample period from July 2021 to December 2025. The results are reported in Figure 4.

The first column of Figure 4 reports mean forecast errors for CPI inflation, the unemployment rate, and real GDP, while the second column reports root-mean-squared forecast errors for the same three data releases.[12] Each panel reports the mean forecast error or RMSE as a function of the number of days until the underlying macroeconomic statistic is released. Forecast errors are computed as the released value of the macroeconomic statistic minus the corresponding forecast. The dark blue line in each panel reports the results for the Kalshi market-implied expectations, the red line reports results for the Blue Chip forecast, and the yellow line reports results for the SPF forecast. In the first column, the dotted blue lines report ± 2-standard-error bands around the Kalshi mean forecast errors.

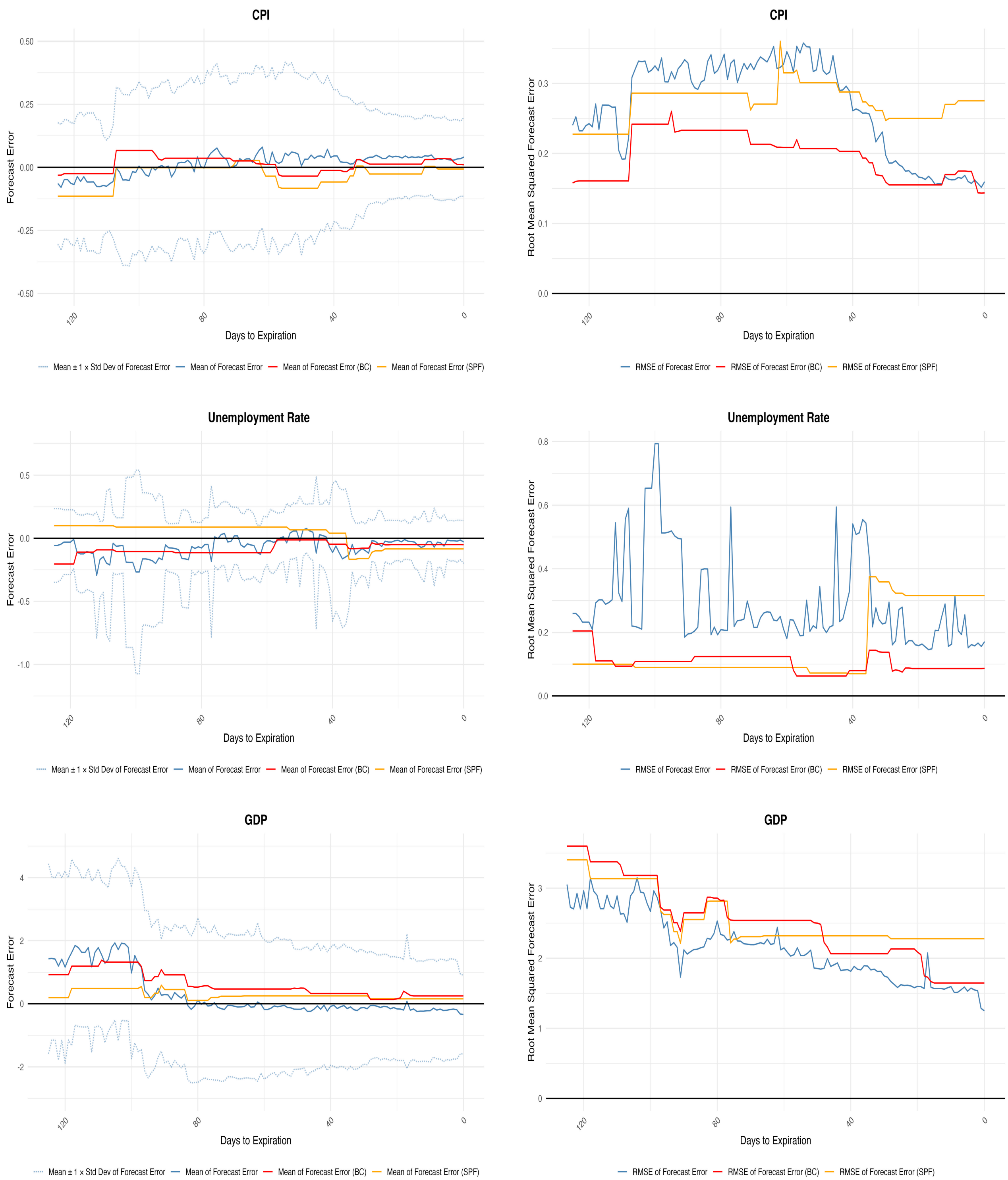
not have a noticeable effect on the calculation. Also note that in the data there exist cases where the price for a contract with higher strike is traded at a higher price than that of an adjacent contract with a lower strike. In those cases, the procedure in equations (1)–(2) would result in a negative implied PDF, which is undesirable for our implied expectation calculation. To address this issue, we estimate prices for all contracts traded on each date using isotonic regression, which ensures monotonicity of prices along the strikes and therefore a positive implied PDF. Specifically, the isotonic regression approach chooses fitted values $\hat{p}_{ths}$ to minimize the weighted sum of squared errors $\sum_s w_{ths}(p_{ths} - \hat{p}_{ths})^2$ subject to the monotonicity constraints $\hat{p}_{ths_1} \geq \hat{p}_{ths_2} \geq \ldots \geq \hat{p}_{ths_K}$ when $s_1 < s_2 < \ldots < s_K$. We use the cumulative trading volume of each contract to compute the weights w_{ths}.

[11] For each event on a given trading day, if there are five or more strikes available, we exclude the smallest and largest strikes and rescale the implied PDFs to ensure that they sum to 1. If there are fewer than five strikes available, then we use all strikes in the expectation calculation.

[12] The Blue Chip survey does not provide forecasts for nonfarm payrolls, and Kalshi has a shorter sample and shorter forecast horizon for nonfarm payrolls, so we do not report results for nonfarm payrolls in Figure 4, although they are provided in the Appendix.

Figure 4. Forecast Errors: Kalshi vs. Blue Chip and SPF

(a) Mean Forecast Errors **(b)** RMSEs



Note: Forecast errors for Kalshi market-implied forecasts (blue lines) vs. Blue Chip (red lines) and Survey of Professional Forecasters (yellow lines) survey-based forecasts, plotted as a function of days until each macroeconomic statistic is released. Column (a): mean forecast errors. Column (b): root-mean-squared forecast errors. Dashed lines in column (a) report ±2 standard error bands around the Kalshi forecast errors.

There are several points to take away from Figure 4. First, all of the forecast errors generally get smaller in absolute value as the number of days to expiration decreases. This is reassuring, since the forecasts should presumably improve as time passes and relevant data comes in. Second, the Kalshi market-implied forecasts fluctuate at much higher frequency than the Blue Chip and SPF forecasts, as evidenced by the higher-frequency movements in the dark blue lines relative to the red and yellow lines. Again, this is as expected, given that the Blue Chip survey is only conducted once per month and the SPF only once per quarter. Third, the Kalshi market-implied forecasts compare very favorably to the Blue Chip and SPF forecasts, with forecast errors that are generally very similar in magnitude, or in some cases even smaller than, the Blue Chip and SPF forecasts. We conclude from this figure that the Kalshi market-implied expectations are generally at least as good as the more traditional, survey-based measures while at the same time being available at much higher, daily frequency.

As previously noted in the Introduction, Diercks et al. (2026) also analyze the accuracy of Kalshi market-implied expectations and forecasting distributions and likewise conclude that those contracts provide high-quality, high-frequency forecasts of macroeconomic outcomes, comparable in accuracy to traditional forecast measures like federal funds futures, SOFR options, the New York Fed's Survey of Market Expectations, and Bloomberg's Consensus forecast. In contrast to Diercks et al. (2026), we use these data to study the Fed Information Effect, below.

Finally, note that the high-frequency nature of the Kalshi market-implied forecasts allows us to track how market expectations evolve essentially continuously, capturing responses to incoming information that are essentially impossible to observe between the monthly Blue Chip or quarterly SPF survey dates.

2.5. Macroeconomic and Monetary Policy Announcements

In addition to the five main macroeconomic events described above—the federal funds rate announcement, CPI release, unemployment rate release, nonfarm payrolls release, and GDP release—we also consider how our Kalshi contracts respond to other major macroeconomic and monetary policy announcements, summarized in Table 2. To determine which additional macroeconomic announcements to consider, we use Bloomberg's "relevance score", which is computed by Bloomberg based on the ratio of the number of alerts set on Bloomberg terminals for a given macroeconomic event relative to the sum of all alerts set for the universe of all U.S. macroeconomic announcements. We include announcements with a Bloomberg relevance score of 80 or more, and classify those announcements accord-

Table 2. Other Macroeconomic Announcements

Event	Definition	Obs
	Panel A: Federal Funds Rate	
Fed Speeches	Speeches and testimony by the Federal Reserve Chair	38
FOMC Minutes Releases	Detailed minutes from previous FOMC meeting	37
	Panel B: CPI	
Producer Price Index (PPI) for Final Demand	BLS report on the change in prices received by domestic producers for their goods and services sold for personal consumption, capital investment, government, and export	51
University of Michigan 1-year Inflation Expectations	University of Michigan Survey of Consumers Report on Inflation Expectations	95
PCE Core Price Index MoM	BEA report on the change in prices that U.S. consumers, or those purchasing on their behalf, pay for goods and services	52
	Panel C: Unemployment Rate and Nonfarm Payrolls	
U.S. Initial Jobless Claims	Department of Labor report on the number of workers applying for unemployment benefits for the first time following job loss	228
ADP Employment Change	Automatic Data Processing Inc., the largest payroll processor, estimate of the number of people employed in the U.S. private sector	51
	Panel D: GDP	
Retail Sales Advance MoM	BEA report on the change in total value of sales at the retail level, a timely indicator of consumer spending, which is itself the largest component of GDP	52

Note: Additional macroeconomic announcements that are likely to affect the Federal Funds Rate, CPI, Unemployment Rate, Nonfarm Payrolls, and GDP Kalshi event contracts. The macroeconomic events are selected based on having a Bloomberg relevance score greater than 80. We classify the macroeconomic events into four categories. "Obs" is the number of release days in the regression sample (July 1, 2021 to December 31, 2025); for the macroeconomic announcements, only releases with a Bloomberg survey forecast are counted.

ing to whether they primarily provide information about the federal funds rate, CPI, the unemployment rate/nonfarm payrolls, or GDP.[13] For additional monetary policy announcements, we also use monetary policy-related speeches and testimony by the Federal Reserve Chair, which were found by Swanson and Jayawickrema (2025) to be a very important source of news about U.S. monetary policy.

[13]We group the unemployment rate and nonfarm payrolls employment together here because news about the labor market in general is very relevant for both of these statistics.

For example, the most relevant CPI-related events are the Producer Price Index (PPI) for final demand, the University of Michigan 1-year Inflation Expectations survey, and the Personal Consumption Expenditures (PCE) Core Price Index, each of which is described briefly in Table 2.

2.6. Federal Funds Futures and Eurodollar Futures Rates

Finally, for some of our analysis below, we use federal funds futures and Eurodollar futures to compute high-frequency monetary policy surprises around FOMC announcements, Federal Reserve Chair speeches, and FOMC minutes releases. We use these futures data for two reasons: First, federal funds futures and Eurodollar futures markets are more liquid than the Kalshi market and can be used to compute intradaily surprises in narrow windows of time around the announcements, which ensures that our monetary policy surprises are not contaminated by any other news that day (Gürkaynak, Sack, and Swanson, 2005).[14] Second, there is already a large literature (including on the Fed Information Effect) that uses futures-based monetary policy surprises, so using the same surprises maximizes our comparability to this previous literature

We also follow Gürkaynak et al. (2005) and compute both a federal funds rate target surprise and a forward guidance surprise for FOMC announcements, using a rotation of the first two principal components of federal funds futures and Eurodollar futures with maturities up to 12 months. For Fed Chair speeches and FOMC minutes releases, we measure just a forward guidance component, using the first principal component of federal funds futures and Eurodollar futures with maturities up to 12 months. There is no federal funds rate target surprise around these latter announcements because the Fed only changes the target rate on the dates of FOMC announcements.

3. Kalshi Trading Volume Responses to Macroeconomic Events

We first estimate the effects of macroeconomic and monetary policy announcements on Kalshi contract trading volumes. Kalshi contracts are traded essentially every day, so we expect trading volumes of macroeconomic and monetary policy event contracts to increase substantially around the times of relevant macroeconomic and monetary policy announcements.

We investigate how contract trading volumes respond to news by estimating regressions

[14] Our intradaily windows are wide enough to capture both the FOMC announcement itself and the press conference afterward.

of the form

$$\log(1+\text{vol}_{i,t}) \;=\; \alpha_i \,+\, \sum_k \beta_k \mathbb{1}_{k,t} \,+\, \gamma \log(1+\text{TTM}_{i,t}) \,+\, \varepsilon_{i,t}, \tag{4}$$

where t indexes trading days and i indexes events (contract expiration dates); $\text{vol}_{i,t}$ denotes the total trading volume across all contracts for event i on day t, $\mathbb{1}_{k,t}$ is an indicator variable for the release of macroeconomic or monetary policy news of type k on day t, $\text{TTM}_{i,t}$ denotes the time to maturity of event i on day t measured in months, α_i is an event-specific fixed effect, and ε_t is a regression residual.[15] We include several major macroeconomic and monetary policy announcement types on the right-hand side of (4), as reported in Table 2, which are expected to increase trading volumes. Recall that trading volumes are typically negatively correlated with time to maturity of the contract (see Figure 2), which motivates its inclusion in (4) as an additional control variable. Our sample for these regressions, and all of our regressions below, runs from July 1, 2021, to December 31, 2025. Note that Kalshi listed only one Federal Funds Rate contract at a time until December 26, 2021, and introduced the full set of monthly contracts on December 27, 2021, so the next-month and longer-term Federal Funds Rate contracts only enter the sample from late December 2021 onward. The longer-term contracts for the other event types enter the sample whenever Kalshi first listed a second event of that type: July 2021 for the CPI, September 2021 for the Unemployment Rate, March 2022 for GDP, and March 2023 for Nonfarm Payrolls.[16]

Table 3 reports the results from regression (4) applied to three types of Kalshi federal funds rate contracts: the front-month contract (column 1), the next-month contract (column 2), and longer-term contracts (column 3), which includes all other federal funds rate contracts after the front- and next-month contracts. Note that nonfarm payrolls and the unemployment rate are always released on the same day, so there is a single indicator variable for those two releases. The Other CPI News, Other Unemployment/Nonfarm Payrolls News, and Other GDP News releases are indicator variables for the events listed in Table 2. Standard errors are reported in parentheses below each coefficient and are clustered by trading date. Appendix Table A1 reports summary statistics of the dependent variable for the three groups of contracts.

[15] Trading volumes can sometimes be zero for a given event on a given day, so $\log(1 + \text{vol}_{i,t})$ is used on the left-hand side of (4). Time to maturity is a real number measured in months and can also get very close to zero, so $\log(1 + \text{TTM}_{i,t})$ is used on the right-hand side of (4). Daily trading volume is measured as the one-day change in the event's cumulative contract volume and is therefore undefined on each event's first trading day; Appendix Table A1 reports its distribution.

[16] Because the pre-December-2021 data add only front-contract observations, and relatively few of them, our regression results are essentially unchanged if we instead begin the sample on December 27, 2021.

Table 3. Kalshi Federal Funds Rate Contract Trading Volume Responses to News

Regressions of log daily Kalshi trading volumes in Federal Funds Rate Contracts on dummy variables for macroeconomic and monetary policy events. The dependent variable is the log of trading volume for three types of Fed Funds Rate contracts: the front contract (column 1), next contract (column 2), and longer-term contracts (column 3), which includes all other Federal Funds Rate contracts after the front and next contracts. Independent variables are dummies that take on the value 1 on the day of release of the corresponding event in each row, corresponding to the events reported in Table 2. Standard errors are clustered by trading date and reported in parentheses (*** p<0.01, ** p<0.05, * p<0.1). Sample: July 1, 2021 to December 31, 2025, except for next and longer contracts, which begin on December 27, 2021. See text for details.

	(1)	(2)	(3)
	Front Contract	Next Contract	Longer Contracts
FOMC Announcement	**1.372*****	**3.401*****	**1.860*****
	(0.514)	(0.352)	(0.454)
Fed Chair Speech	**1.037*****	**0.903****	**0.957****
	(0.257)	(0.420)	(0.406)
FOMC Minutes	**0.996*****	0.830	0.452
	(0.338)	(0.505)	(0.377)
CPI	**1.410*****	**1.769*****	**1.290*****
	(0.307)	(0.345)	(0.336)
Other CPI News	**0.499****	**0.705*****	**0.544*****
	(0.206)	(0.228)	(0.180)
Unemployment Rate/Nonfarm Payrolls	**1.813*****	**2.655*****	**1.636*****
	(0.296)	(0.333)	(0.355)
Other Unemployment/NFP News	**0.614*****	**1.159*****	**0.673*****
	(0.163)	(0.202)	(0.150)
GDP	0.387	−0.811	0.242
	(0.469)	(0.751)	(0.587)
Other GDP News	0.513	**0.714***	0.402
	(0.366)	(0.409)	(0.316)
log Months to Maturity	**0.867*****	−**2.939*****	−**2.691*****
	(0.322)	(0.637)	(0.142)
Event Fixed Effects	Yes	Yes	Yes
Observations	1,579	1,465	7,436
R^2	0.615	0.435	0.268

As expected, due to the direct connection between Kalshi Federal Funds Rate contracts and FOMC meetings, trading activity increases very significantly on days when a Federal Open Market Committee (FOMC) announcement occurs. Over our sample from July 2021 to December 2025, the largest effect is observed for the next-month contract, with a coefficient of about 3.40, implying that trading volumes are about $e^{3.40} = 30$ times higher on those dates, relative to dates on which no other announcements occurred. This effect is highly statistically significant, with a t-statistic greater than 9. The coefficient for the longer-term Federal Funds Futures contracts in column (3) is also very large and highly statistically significant.

Kalshi Federal Funds Rate contract trading volumes also increase substantially on other Fed-related event days, such as the dates of speeches by the Federal Reserve Chair and FOMC minutes releases. The magnitudes here are a bit less than for FOMC announcements themselves, with trading volumes about 2 to 3 times larger than on non-event days; the effects are statistically significant for Fed Chair speeches in all three columns and for FOMC minutes releases in the front contract.

Kalshi Federal Funds Rate contracts are also traded heavily on other major macroeconomic announcement dates. For example, CPI and unemployment rate/nonfarm payrolls announcements lead to an increase in Fed Funds Rate contract trading volumes by a factor of about 4 to 14, relative to non-event days, and other CPI news (i.e., the PPI and PCE inflation announcements and the Michigan inflation-expectations survey) and other unemployment/nonfarm payrolls news lead to increases of about 65 to 220 percent.

Finally, trading volumes are lower the greater the time to contract maturity, with a doubling in months to maturity causing a decrease in trading volumes by a factor of about 4.9 for the next-month and longer-term contracts, and somewhat less than this for the front contract.

Overall, the results in Table 3 confirm that Kalshi Federal Funds Rate contract trading volumes respond very substantially to relevant monetary policy and macroeconomic announcements.

In Table 4, we repeat this analysis for the responses of daily Kalshi contract trading volumes for the CPI, Unemployment Rate, Nonfarm Payrolls, and GDP contracts to the same set of announcements.[17] As expected, CPI contract trading volumes spike on the days of

[17] Note that when Kalshi first introduced the Nonfarm Payrolls contracts in 2023, the first Nonfarm Payrolls event was sometimes more than 37 days in the future. For Nonfarm Payrolls, we therefore call a contract the "front" contract only if it is the contract with the nearest release date and that release is 37 or fewer days away; otherwise we call it a "longer-term" contract.

CPI data releases, Unemployment Rate and Nonfarm Payrolls contract volumes spike on the days of unemployment rate and nonfarm payrolls releases, and GDP contract volumes spike on the days of GDP releases. These responses are all statistically significant, with the exception of the front GDP contract and the front CPI contract.[18] CPI contract trading volumes also increase substantially in response to almost all of the other event days listed in Table 4, and Unemployment Rate, Nonfarm Payrolls, and GDP contract trading volumes also increase substantially on many of the other event days as well. Finally, as in Table 3, trading volumes decrease substantially as time to contract maturity increases.

Overall, the results in Table 4 are consistent with those in Table 3 and show a substantial increase in Kalshi macroeconomic event contract trading volumes around relevant data releases. This is reassuring for our analysis below, because even several weeks or months prior to contract expiration, when liquidity is lower, liquidity increases substantially exactly when we are most interested in the Kalshi contract prices—around the times of other major macroeconomic data releases and monetary policy announcements.

[18]The front CPI release-day response is insignificant only because of the newly introduced, thinly traded CPI contracts in the second half of 2021, when daily volume changes were large and erratic regardless of data releases; from December 27, 2021, onward the coefficient is 1.15 (s.e. 0.23) and highly significant.

Table 4. Kalshi Macroeconomic Contract Trading Volume Responses to News

Regressions of log daily Kalshi trading volumes in CPI, Unemployment Rate, Nonfarm Payrolls, and GDP contracts on dummy variables for macroeconomic and monetary policy events. "Front" contract refers to the contract nearest to maturity, while "Longer-term" contracts include all contracts beyond the front contract. Independent variables are dummies that take on the value 1 on the release dates of the events in each row, corresponding to the events listed in Table 2. Standard errors are clustered by trading date and reported in parentheses (*** p<0.01, ** p<0.05, * p<0.1). Sample: July 1, 2021 to December 31, 2025, except for Nonfarm Payrolls contracts, which begin in March 2023. See text for details.

	CPI		Unemployment Rate		Nonfarm Payrolls		GDP	
	Front	Longer-term	Front	Longer-term	Front	Longer-term	Front	Longer-term
FOMC Day	**1.024*****	0.353	**0.718****	0.427	**0.867****	0.265	**1.096*****	**1.613***
	(0.325)	(0.262)	(0.305)	(0.380)	(0.390)	(0.373)	(0.331)	(0.964)
Fed Chair Speech	**0.661****	0.353	**0.631****	0.484	0.651	1.148	0.234	**1.345***
	(0.331)	(0.296)	(0.320)	(0.383)	(0.533)	(1.149)	(0.378)	(0.773)
FOMC Minutes	**0.907*****	0.157	0.220	0.062	**1.215*****	0.795	0.316	0.738
	(0.340)	(0.315)	(0.309)	(0.261)	(0.349)	(0.813)	(0.373)	(0.751)
CPI	0.478	**2.237*****	**0.888*****	**0.405***	**1.114****	0.247	**0.629****	0.624
	(0.325)	(0.403)	(0.288)	(0.238)	(0.446)	(1.094)	(0.314)	(0.733)
Other CPI News	**0.724*****	−0.008	**0.407****	0.112	0.220	**1.010*****	**0.653*****	0.154
	(0.170)	(0.144)	(0.192)	(0.175)	(0.250)	(0.385)	(0.189)	(0.295)
Unemployment Rate/Nonfarm Payrolls	**0.782*****	**0.331***	**0.881****	**3.050*****	**1.874*****	**3.747*****	**0.728****	−0.068
	(0.271)	(0.169)	(0.400)	(0.371)	(0.343)	(0.755)	(0.334)	(0.352)
Other Unemployment/NFP News	**0.291***	**0.340****	**0.898*****	0.116	**1.124*****	0.361	**0.628*****	0.022
	(0.150)	(0.133)	(0.159)	(0.173)	(0.216)	(0.275)	(0.156)	(0.219)
GDP	−0.019	−**0.431***	−0.191	0.566	0.638	**2.120****	0.025	**3.184*****
	(0.375)	(0.244)	(0.604)	(0.496)	(0.535)	(1.038)	(0.747)	(0.813)
Other GDP News	0.429	0.205	0.365	−0.128	−0.139	−1.103	**1.481*****	−0.264
	(0.354)	(0.247)	(0.317)	(0.198)	(0.444)	(0.924)	(0.288)	(0.513)
log Months to Maturity	−**2.271*****	−**1.960*****	−**3.877*****	−0.100	−**3.980*****	−**2.545***	−**1.791*****	−**2.692*****
	(0.284)	(0.129)	(0.321)	(0.169)	(0.423)	(1.339)	(0.161)	(0.580)
Event fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,644	3,330	1,610	1,085	949	586	1,610	367
R^2	0.525	0.376	0.467	0.456	0.463	0.565	0.372	0.446

4. Kalshi Market Expectations of Monetary Policy's Effects on the Macroeconomy

We now turn to one of the central research questions of this paper: How do the Kalshi market-implied expectations of future inflation, unemployment, nonfarm payrolls, and GDP respond to monetary policy announcements? As discussed above, standard survey-based data on market expectations of macroeconomic variables, such as the Blue Chip or SPF surveys of forecasters, are only collected and released at a monthly or quarterly frequency. As a result, it's very difficult to measure how those expectations respond to specific events like monetary policy announcements, because so much other confounding information is released every month, leading to the omitted variables problem discussed at length in Bauer and Swanson (2023a). In contrast, the high frequency of our Kalshi contract data allows us to effectively isolate the effects of particular events, like FOMC announcements or Fed Chair speeches, and see how they affect market expectations. For example, Figure 1 in the Introduction provided a good example of the Kalshi market-implied forecast for GDP around the Federal Reserve's major monetary policy tightening announcement on June 15, 2022.

To estimate the effects of monetary policy announcements on the Kalshi market-implied expectations, we run regressions of the form:

$$\Delta Y_{i,t} \;=\; \beta_{ffr}\,(\Delta \text{FFR}_t \times \text{FOMCDays}_t) \;+\; \beta_{fg}'\,(\Delta \text{FG}_t \times \text{FedDays}_t) + \;\alpha_i \;+\; \varepsilon_{i,t} \tag{5}$$

where $\Delta Y_{i,t}$ denotes the daily change in the Kalshi market-implied expectation for a given macroeconomic variable (CPI, unemployment, nonfarm payrolls, or GDP) for event i on day t, ΔFFR_t measures the surprise change in the current federal funds rate target based on the 30-minute change in federal funds futures rates, ΔFG_t measures the surprise change in forward guidance based on intradaily changes in federal funds futures and SOFR futures rates, FOMCDays_t is an indicator variable for the days of FOMC announcements, FedDays_t is a set of three indicator variables for each of the three types of Fed event days (FOMC announcements, Fed Chair speeches, and FOMC minutes releases), α_i is an event-specific fixed effect, and $\varepsilon_{i,t}$ is a regression residual. Recall that the current federal funds rate target is only changed along with an FOMC announcement in our sample, so the ΔFFR_t variable is only nonzero on FOMC announcement days and is computed in the same way as in Kuttner (2001), Gürkaynak et al. (2005), and Swanson and Jayawickrema (2025). For Fed Chair speeches and FOMC minutes releases, we measure forward guidance as the first principal component of intradaily changes in SOFR futures rates with 1 year or less to maturity around the corresponding announcements, as in Swanson and Jayawickrema (2025). For FOMC announcements, we measure forward guidance in the same was as in Gürkaynak et al. (2005) and Swanson and Jayawickrema (2025).[19]

Our primary parameters of interest are the β coefficients, which measure the relationship between daily changes in the expected federal funds rate on Fed announcement days and daily changes in macroeconomic expectations. For example, for GDP expectations, a negative estimate of β would imply that the market associates tighter monetary policy news with weaker future GDP, consistent with standard macroeconomic model predictions, while a positive estimate of β would imply that the market associates tighter monetary policy with *stronger* future GDP, consistent with the literature on the "Fed Information Effect".

Table 5 presents our estimates of β for Kalshi market-implied CPI, Unemployment Rate, Nonfarm Payrolls, and GDP expectations; Appendix Table A2 reports summary statistics of the estimation sample. As in Table 4, the "front" contract refers to the contract that is closest to expiration, while "longer-term" contracts include all contracts with expirations beyond the front contract. An advantage of distinguishing between the front and longer-term contracts here is that a change in monetary policy might be expected to take some time to affect these macroeconomic variables, so that we might see little or no effect of monetary policy on the front contract but a more substantial effect on the longer-term contracts. The coefficients in Table 5 are in units of percentage point change in expectations per percentage point change in the given interest rate, with the exception of Nonfarm Payrolls, which is in units of millions of jobs per percentage point change in the interest rate.

[19] For FOMC announcements, we measure ΔFFR_t and ΔFG_t using exactly the same methods as the "target" and "path" factors from Gürkaynak et al. (2005) and Swanson and Jayawickrema (2025), based on 30-minute changes in federal funds futures and SOFR futures rates around those announcements. The value of ΔFG_t on FOMC announcement days is the sum of the ΔFG_t values for the FOMC announcement itself and for the post-FOMC press conference, since both occur on the same day.

Table 5. Kalshi Market-Implied Expectations Responses to Monetary Policy News

Responses of Kalshi market-implied expectations of macroeconomic variables to monetary policy announcements. The "front" contracts are those for the event with the nearest release date, and "longer-term" contracts are those for all later events. "FFR Target Surprise" is the surprise change in the current federal funds rate, which is non-zero only on FOMC announcement days; "Forward Guidance" is computed as in Gürkaynak et al. (2005) and Swanson and Jayawickrema (2025). "FOMC Minutes" days are the release days of the FOMC minutes. Standard errors are clustered at the trading date level and reported in parentheses (*** p<0.01, ** p<0.05, * p<0.1). Sample: July 1, 2021 to December 31, 2025, except for Nonfarm Payrolls contracts, which begin in March 2023. See notes to Table 4 and text for details.

	CPI		Unemployment Rate		Nonfarm Payrolls		GDP	
	Front	Longer-term	Front	Longer-term	Front	Longer-term	Front	Longer-term
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
FFR Target Surprise x FOMC Announcement	0.062	$\mathbf{-0.975}^{***}$	0.046	−1.521	$\mathbf{-0.422}^{**}$	0.009	0.174	$\mathbf{-5.222}^{*}$
	(0.122)	(0.347)	(0.264)	(1.222)	(0.168)	(0.200)	(1.758)	(3.076)
Forward Guidance x FOMC Announcement	−0.009	$\mathbf{-0.385}^{**}$	0.114	−1.158	$\mathbf{-0.359}^{**}$	−0.006	−0.460	−1.943
	(0.087)	(0.167)	(0.130)	(0.889)	(0.161)	(0.072)	(0.711)	(1.675)
Forward Guidance x Fed Chair Speech	0.019	$\mathbf{-0.164}^{**}$	−0.029	0.114	−0.129	−0.009	−1.939	$\mathbf{-8.954}^{**}$
	(0.175)	(0.080)	(0.133)	(0.172)	(0.139)	(0.072)	(1.586)	(3.820)
Forward Guidance x FOMC Minutes	−0.084	0.190	0.557	$\mathbf{-1.188}^{*}$	0.524	−0.143	−3.190	0.865
	(0.239)	(0.150)	(0.586)	(0.661)	(0.390)	(0.219)	(3.129)	(1.074)
Event FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,645	3,343	1,615	1,096	950	597	1,613	372
R^2	0.009	0.009	0.004	0.070	0.008	0.056	0.004	0.067

Looking first at the effects of FOMC announcements (which include post-FOMC press conferences) in the first two rows of Table 5, we estimate a strong and significantly negative response of Kalshi market-implied CPI expectations to federal funds rate and forward guidance changes, but only for the longer-term CPI contracts. Consistent with the intuition discussed above, this is reasonable if we think monetary policy takes some time to affect inflation, so that the front CPI contract is not affected but later contracts are. We estimate a similar negative response for Nonfarm Payrolls expectations, albeit one that is statistically significant only for the front contracts. Finally, we estimate a large, negative, and statistically significant response of Kalshi market-implied GDP expectations to federal funds rate surprises, but only for the longer-term GDP contracts.

All of these estimates are consistent with standard macroeconomic models and VARs, with tighter monetary policy leading to a weaker economy and lower prices in the future. They are also generally inconsistent with the standard Fed Information Effect story, which has been used to explain positive coefficient estimates for these variables in lower-frequency, monthly regressions (e.g., Romer and Romer, 2000; Campbell et al., 2012; Nakamura and Steinsson, 2018). Note, however, that our findings here do not completely rule out the possible existence of a Fed Information Effect, only that any such information effect is less important over our sample than the standard transmission channels of monetary policy, in the views of Kalshi market participants.

The results for Fed Chair speeches in Table 5 are similar, with a statistically significant, albeit smaller, negative effect on the Kalshi longer-term CPI expectations. The effect on longer-term GDP expectations is also significant and larger, but is driven by a single outlier, so we do not take much away from that estimate.[20] Again, these negative coefficients are consistent with the standard transmission channels of monetary policy, and are generally not consistent with a large Fed Information Effect.

FOMC minutes releases in Table 5 generally do not have significant effects on the Kalshi market-implied CPI, nonfarm payrolls, and GDP expectations, although they do have a borderline significantly negative effect on longer-term unemployment rate expectations. The sign of this effect is generally opposite to what would be predicted by standard macroeconomic models and thus does lend some support to the Fed Information Effect story. Thus, to the extent that there is any evidence of a Fed Information Effect in our data, it is here in the FOMC minutes releases rather than in FOMC announcements themselves or the Fed Chair's speeches. Intuitively, the idea would be that the FOMC minutes, which

[20]The coefficient for longer-term GDP expectations in Table 5 is based on only five observations and is driven by a single outlier on June 22, 2023, that had only minor implications for monetary policy according to *Wall Street Journal* reporting at the time. See Appendix C.

are typically 10–15 pages long and discuss the state of the economy at some length, reveal information to the market about unemployment that the market did not previously possess. However, given the weak significance of this coefficient in the table, the evidence supporting this story is quite limited.

4.1. Pooled Regression Results

To provide a concise summary of how monetary policy affects macroeconomic expectations, and to increase the statistical power of our estimates over our relatively short sample, we pool our four macroeconomic contracts together and analyze the effects of monetary policy announcements on the Kalshi market-implied expectations for these macroeconomic variables in pooled regressions.

Different macroeconomic variables have inherently different average sensitivities to interest rate changes (Swanson and Williams, 2014; Elenev, Law, Song, and Yaron, 2024), so we start by estimating the average correlation of each macro variable m (CPI, Unemployment Rate, Nonfarm Payrolls, GDP) with interest rate changes, based on event-level panel data using our whole sample:

$$\Delta Y_{i,t}^{m,h} \;=\; \beta_{near}^{m,h}\,\Delta\mathrm{FFR}_t^{near} \;+\; \beta_{far}^{m,h}\,\Delta\mathrm{FFR}_t^{far} + \alpha_i^{m,h} + \varepsilon_{i,t}^{m,h} \tag{6}$$

where t indexes trading days, i Kalshi events (data release announcements), m the macro variable, and h the contract horizon (front or longer-term). $\Delta\mathrm{FFR}_t^{near}$ and $\Delta\mathrm{FFR}_t^{far}$ denote the daily changes in near-term (FF2) and longer-term (SOFR4) interest rates, respectively, $\Delta Y_{i,t}^{m,h}$ is the standardized daily change in the market-implied expectation for event i (divided by each series' standard deviation), and the regression is estimated separately for each macro variable m and horizon h.

We use the estimated coefficients $\hat{\beta}_{near}^{m,h}$ and $\hat{\beta}_{far}^{m,h}$ from (6) to construct weights $\omega^{m,h}$ for macro variable m and horizon h,

$$\omega^{m,h} \;=\; \frac{1}{|\overline{\beta}^{m,h}|}, \tag{7}$$

where $\overline{\beta}^{m,h} = \frac{1}{2}(\hat{\beta}_{near}^{m,h} + \hat{\beta}_{far}^{m,h})$ is the average of the estimated near-term and longer-term rate sensitivities for macro variable m at horizon h. The idea is that if two macroeconomic statistics m_1 and m_2 have different average sensitivities to interest rates, they should each be normalized by that average sensitivity when running a pooled regression of the statistics on monetary policy announcements. The weights $\omega^{m,h}$ perform that normalization. The weights are based on the absolute value of $\overline{\beta}^{m,h}$ and are thus all positive; the inverse relationship between the unemployment rate and the other three macroeconomic variables is instead handled directly, by reversing the sign of the standardized unemployment rate series in the pooled regressions, as described below.[21]

The pooled regression specification corresponds closely to (5), with the target surprise interacted with FOMC announcement days and the forward guidance surprise interacted with all three types of Fed announcement days:

$$\Delta\widetilde{Y}_{i,t}^{m} \;=\; \beta_{ffr}(\Delta\text{FFR}_t \times \text{FOMCDays}_t) \,+\, \beta_{fg}'(\Delta\text{FG}_t \times \text{FedDays}_t) + \alpha_i^m + \varepsilon_{i,t}^m, \qquad (8)$$

where $\Delta\widetilde{Y}_{i,t}^{m}$ denotes the standardized daily change in macroeconomic expectations (divided by each series' standard deviation), with the unemployment rate series multiplied by -1 so that, for all four series, a positive value of $\Delta\widetilde{Y}$ corresponds to an improving economic outlook (higher expected inflation, output, and payrolls, and lower expected unemployment); the observations are weighted by $\omega^{m,h}$ in the estimation. Here ΔFFR_t and ΔFG_t are the federal funds rate surprise and forward guidance surprise as computed in Gürkaynak et al. (2005) and Swanson and Jayawickrema (2025), and α_i^m denotes event-by-macro-series fixed effects. The coefficients of interest, β, can be interpreted as the number of standard deviations by which macroeconomic expectations change on the corresponding Fed event days, per percentage point change in the interest rate factor.

Table 6 reports the results. Consistent with the individual event-level results in Table 5, the pooled regressions show that tighter monetary policy leads to significant downward revisions in macroeconomic expectations, and that these effects are concentrated in longer-term contracts. Federal funds rate surprises on FOMC announcement days are associated with a significant decline in longer-term expectations (-11.7 standard deviations per percentage point, column 3), while the effect on front contracts is essentially zero (column 2). Forward guidance surprises on FOMC days show a similar pattern, with a significant negative effect concentrated in the longer-term contracts.

The effects of Fed Chair speeches on macroeconomic expectations are similar to those of FOMC announcements, with a significant negative effect concentrated in the longer-term contracts, consistent with the individual results for the CPI and GDP in Table 5. However, FOMC minutes releases do not have significant effects at either the front or longer-term contract horizons.

Overall, the pooled results in Table 6 are consistent with the standard transmission chan-

[21]These estimated sensitivities and the resulting weights are reported in Appendix Table A3. For the pooled regression across all horizons (column 1 of Table 6), we further average across horizons to obtain $\omega^m = 1/|\overline{\beta}^m|$, where $\overline{\beta}^m$ averages over both rate types and both horizons.

Table 6. Pooled Kalshi Market Expectations Responses to Monetary Policy News

Pooled regression estimates of the effects of monetary policy announcements on Kalshi market-implied expectations of macroeconomic variables, pooling together CPI, Unemployment Rate, Nonfarm Payrolls, and GDP contracts. The dependent variable is the standardized daily change in market-implied expectations (divided by each series' standard deviation), with the unemployment rate series entering with its sign reversed so that positive changes indicate an improving economic outlook for all four series. Observations are weighted by the series-by-horizon weights ω of equation (7), reported in Appendix Table A3. Standard errors are clustered at the trading date level and reported in parentheses (*** p<0.01, ** p<0.05, * p<0.1). Sample: July 1, 2021 to December 31, 2025, except for Nonfarm Payrolls contracts, which begin in March 2023. See notes to Table 5 and text for details.

	Standardized Pooled Kalshi Market-Implied Macro Expectations		
	All Horizons	Front	Longer-term
	(1)	(2)	(3)
FFR Target Surprise x FOMC Announcement	**−5.875****	0.289	**−11.663*****
	(2.878)	(1.437)	(4.051)
Forward Guidance x FOMC Announcement	**−2.839***	−0.068	**−4.747****
	(1.695)	(0.742)	(2.010)
Forward Guidance x Fed Chair Speech	**−1.789*****	−1.438	**−2.008****
	(0.637)	(1.424)	(1.004)
Forward Guidance x FOMC Minutes	0.372	0.489	1.797
	(1.200)	(2.183)	(1.910)
Event FE	Yes	Yes	Yes
Observations	11,231	5,823	5,408
R^2	0.004	0.004	0.015

nels of monetary policy, with negative effects on the Kalshi market-implied expectations of macroeconomic variables that are particularly pronounced for contracts beyond the front contract. This is exactly the kind of pattern that would be predicted by standard macroeconomic models and VARs. In contrast, the standard Fed Information Effect narrative—that FOMC announcements cause market expectations of macro variables to move in a puzzling, opposite direction—is inconsistent with these estimates.

4.2. Federal Reserve Information and Non-Yield Shock Decompositions

Our results above all use the *total* monetary policy surprise around FOMC announcements, Fed Chair speeches, and FOMC minutes releases as explanatory variables. This approach is consistent with many of the most prominent studies of the Fed Information Effect, such as Romer and Romer (2000), Campbell et al. (2012), Nakamura and Steinsson (2018), and Bauer and Swanson (2023a). Nevertheless, some authors, such as Jarocinski and Karadi (2020), have argued that the information component of FOMC announcements is not constant but rather varies over time. Here we repeat our main analysis above using the Jarocinski and Karadi (2020) decomposition of FOMC announcement surprises into "pure monetary policy" and "central bank information" shocks and related estimates of a "Fed non-yield shock" by Boehm and Kroner (2024).

The Jarocinski and Karadi (2020) decomposition uses the high-frequency comovement of short-term interest rates and stock prices in a narrow window around each FOMC announcement. The idea is that a pure monetary policy shock moves short-term interest rates and stock prices in opposite directions (consistent, e.g., with Bernanke and Kuttner, 2005), while a Fed information shock, in which the Fed reveals information about the economy's strength, moves short-term interest rates and stock prices together in the same direction. We use the Jarocinski-Karadi estimated monetary policy (MP) and central-bank-information (CBI) shocks (median-rotation version) provided on Marek Jarocinski's website and refer the reader to their paper for additional details.

Boehm and Kroner (2024) show that, even after controlling for interest rate changes along the entire yield curve around FOMC announcements, there is still a large component left that moves stock prices, exchange rates, corporate bond spreads, and international financial markets. They call this remaining component the "Fed Non-Yield shock," and note that it is orthogonal to interest rate changes (by definition) but not random noise because it moves many risky asset prices together systematically and significantly. Nevertheless, Boehm and Kroner do not interpret the "Fed non-yield shock" as an information shock, because its correlation with the Jarocinski-Karadi information shock is very low. Instead, Boehm and Kroner offer an interpretation in which FOMC announcements potentially remove tail risk scenarios from the economic outlook, increasing financial market risk appetite without affecting the expected (mean) path of interest rates. We use the Boehm-Kroner "Fed non-yield shock" downloaded from Christoph Boehm's website and refer the reader to their paper for additional details.

Note that both the Jarocinski-Karadi decomposition and Boehm-Kroner non-yield shock are computed for FOMC announcements only, so our analysis here focuses only on FOMC announcements (i.e., excluding Fed Chair speeches and FOMC minutes releases). We reestimate regression (5), replacing our previous measures of the federal funds rate and forward guidance surprises, ΔFFR and ΔFG, with the Jarocinski-Karadi decomposition,

$$\Delta Y_{i,t} = \beta_{MP} \left(\text{MP}_t \times \text{FOMCDays}_t\right) + \beta_{CBI} \left(\text{CBI}_t \times \text{FOMCDays}_t\right) + \alpha_i + \varepsilon_{i,t}, \tag{9}$$

or adding the Boehm-Kroner non-yield shock to the regression:

$$\begin{aligned}\Delta Y_{i,t} = \beta_{ffr}(\Delta\text{FFR}_t \times \text{FOMCDays}_t) + \beta_{fg} \left(\Delta\text{FG}_t \times \text{FOMCDays}_t\right) \\ + \beta_{BK}(\text{BK}_t \times \text{FOMCDays}_t) + \alpha_i + \varepsilon_{i,t}.\end{aligned} \tag{10}$$

As before, α_i is an event fixed effect and standard errors are clustered at the trading-day level. Under the Fed Information Effect, a positive information shock should raise expectations of inflation, output, and payrolls and lower expected unemployment. The effects of the Boehm-Kroner non-yield shock are unclear but should have a significant positive effect on risky asset prices, consistent with its effects on stocks, credit spreads, foreign risky assets, and foreign currencies.

The results are reported in Table 7. The first panel reports results for the Jarocinski and Karadi (2020) decomposition, while the second panel reports results for Boehm and Kroner (2024) non-yield shock. As before, we consider regressions for the "front" and "longer-term" Kalshi market-implied expectations for the CPI, unemployment rate, nonfarm payrolls, and GDP releases.

The Jarocinski-Karadi shocks have strikingly little systematic effect on the Kalshi market-implied expectations (Panel A). The central bank information shock is statistically significant only for front-month CPI expectations, with no consistent pattern across the other series or horizons. Although the effect on the front Kalshi CPI expectation is positive, consistent with the Fed Information Effect, the lack of a response of the other variables casts some doubt on the true macroeconomic information content of the shock. Given how JK information shock was defined—based on stock-market responses to FOMC announcements—this result suggests that what Jarocinski and Karadi called an "information" shock may instead reflect changes in market risk appetite and stock market risk premia, similar to the Boehm-Kroner non-yield shock.

Table 7. Kalshi Market-Implied Expectations Responses to Fed Information and Non-Yield Shocks

Responses of Kalshi market-implied expectations of macroeconomic variables to the Jarocinski and Karadi (2020) pure monetary-policy (MP) and central-bank-information (CBI) shocks (Panel A) and Boehm and Kroner (2024) Fed non-yield shock (Panel B). "Front" contract refers to the contract nearest to maturity, while "Longer-term" contracts include all contracts beyond the front contract. Standard errors are clustered at the trading-day level and reported in parentheses (*** p<0.01, ** p<0.05, * p<0.1). Sample: July 1, 2021 to December 31, 2025, except Nonfarm Payrolls begins in March 2023 and the BK Non-Yield shock ends in July 2025 due to data availability.

	CPI		**Unemployment Rate**		**Nonfarm Payrolls**		**GDP**	
	Front	Longer-term	Front	Longer-term	Front	Longer-term	Front	Longer-term
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(A) Jarociński–Karadi Decomposition								
JK Pure MP	0.055	−0.199	0.099	**−1.666***	−0.282	0.011	−0.477	−0.886
	(0.120)	(0.432)	(0.408)	(0.921)	(0.232)	(0.138)	(1.326)	(2.789)
JK CB Information	**0.231****	−0.341	−0.147	1.633	−0.110	0.014	0.522	−3.866
	(0.117)	(0.324)	(0.200)	(1.142)	(0.158)	(0.061)	(0.885)	(2.828)
R^2	0.011	0.006	0.003	0.077	0.004	0.056	0.002	0.062
(B) Boehm–Kroner Fed Non-Yield Shock								
FFR Target	0.059	**−1.172*****	−0.059	−0.915	−0.174	0.009	0.359	**−8.550*****
	(0.115)	(0.368)	(0.258)	(1.380)	(0.219)	(0.034)	(1.475)	(2.081)
Forward Guidance	−0.013	**−0.509*****	0.024	−0.792	−0.169	−0.006	−0.317	**−4.015*****
	(0.078)	(0.173)	(0.117)	(0.943)	(0.235)	(0.011)	(0.681)	(1.118)
BK Non-Yield	−0.008	−0.189	−0.192	0.417	0.215	0.002	0.309	**−4.920****
	(0.062)	(0.197)	(0.150)	(0.525)	(0.195)	(0.144)	(0.878)	(2.052)
R^2	0.009	0.009	0.004	0.069	0.007	0.056	0.002	0.066
Event FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,645	3,343	1,615	1,096	950	597	1,613	372

In the Boehm-Kroner non-yield shock regressions (Panel B), the non-yield shock likewise does not have any statistically significant effects on Kalshi market-implied expectations, with the exception of longer-term GDP. (By contrast, the effects of the federal funds rate target and forward guidance changes remain negative and highly significant for longer-term CPI and GDP expectations, as in Table 5.) Again, this result is consistent with Boehm and Kroner's interpretation of their shock as *not* reflecting Fed information, but rather an increase in the market's appetite for risky assets.

For both the Jarocinski-Karadi and Boehm-Kroner, shocks, the lack of significant effects on the Kalshi market-implied expectations is exactly the pattern one would expect if the stock-price comovement that identifies these shocks reflects shifts in risk premia rather than genuine news about fundamentals. A pooled specification that stacks the four series to gain power tells the same story (Internet Appendix Table IA.6): the pure monetary policy shock retains the standard, negative transmission sign, while the Jarocinski and Karadi (2020) information shock has essentially no effect on fundamental expectations. Taken together, these results reinforce our central finding of at most a small Fed Information Effect in Kalshi market-implied expectations, and show that event-contract data can separate the risk-premium-like component of "information" shocks from any genuine news content.

5. Discussion

Overall, our estimates in the previous section are consistent with the standard transmission mechanism from monetary policy to the economy in macroeconomic models and VARs, in which higher interest rates lead to lower output and employment and lower inflation. Our results here thus provide substantial new evidence against the very large Fed Information Effect that has been proposed by some previous authors (e.g., Romer and Romer, 2000; Campbell et al., 2012; Nakamura and Steinsson, 2018) to explain puzzling positive coefficients in lower-frequency, monthly versions of regression equation (5) above.

Previous authors could only estimate lower-frequency versions of regression (5) because standard data on macroeconomic expectations, like the Blue Chip survey or the Survey of Professional Forecasters, is only available at a monthly or quarterly frequency. The problem with running regressions like (5) at monthly or lower frequency is that there is a great deal of macroeconomic and financial information released every month beyond just the Fed's monetary policy announcements. As argued by Bauer and Swanson (2023a,b), those other macroeconomic and financial releases are important omitted variables in those monthly regressions and could be driving the puzzling, positive results estimated by previous authors. In fact, when Bauer and Swanson (2023a,b) include those omitted variables in the monthly forecast revision regression, they get a much larger R^2, smaller standard errors, and show that the puzzling positive values for β estimated by previous authors is reversed, making it consistent with standard macroeconomic models and VARs.

Our use of high-frequency data from Kalshi's prediction markets has some significant advantage over these previous studies and provides us with a new perspective on their results. Unlike the Blue Chip survey or Survey of Professional Forecasters, Kalshi contracts are traded much more frequently, typically multiple times per day. This high frequency enables us to essentially isolate the effects of specific economic events like monetary policy announcements on those Kalshi market-implied expectations with minimal confounding influences. As shown in Tables 3 and 4, Kalshi trading volumes increase substantially around major macroeconomic and monetary policy announcements, suggesting that market participants actively revise their expectations in response to new information. Thus, in contrast to Bauer and Swanson (2023a,b), we don't even need to control for other variables on the right-hand side of (5) because the narrow, one-day forecast change on the left-hand side already effectively excludes other macroeconomic and financial news releases.

While Bauer and Swanson (2023a,b) run monthly version of regression (5) with additional controls on the right-hand side for macroeconomic and financial data, and estimate negative values of β, we run regressions (5) at daily frequency—which then requires no additional right-hand side controls—and estimate similarly negative values for β. Our results thus complement those of Bauer and Swanson (2023a,b).

It's important to note, however, that these results do not completely rule out all possible versions of a "Fed Information Effect" more generally. Our evidence here, and that in Bauer and Swanson (2023a,b), only rules out the extremely strong information effects that would generate positive coefficients β in regressions like (5). More generally, monetary policy announcements by the Fed could potentially reveal some information about the state of the economy that the private sector didn't previously have, but the amount of that information might be so small that it does not change the sign of the coefficients β estimated in regression (5). Alternatively, the Fed Information Effect might be small on average—consistent with our estimates above—but might be large on a small number of isolated dates. This latter version of the Fed Information Effect is the one promoted by Jarocinski and Karadi (2020) and Lunsford (2020), and our results here, and those in Bauer and Swanson (2023a,b), do not completely rule that possibility out.

6. Conclusions

We use high-frequency data from Kalshi event contracts to investigate how monetary policy announcements affect market-implied expectations of macroeconomic variables. We show first that Kalshi's prediction markets are sufficiently liquid to provide meaningful signals regarding macroeconomic expectations, with trading volumes spiking significantly around relevant macroeconomic data releases and monetary policy announcements. The high-frequency nature of the Kalshi market data—with typically many trades per event per day—allows us to more directly test competing theories of monetary policy transmission without relying on potentially problematic survey-based measures. This constitutes a significant methodological advancement and a new perspective in the literature estimating monetary policy's effects on macroeconomic variables and macroeconomic expectations.

Our findings strongly support the standard transmission channels from monetary policy to the economy, consistent with standard macroeconomic models and VARs—that is, higher interest rates cause output, employment, and inflation to fall—and are not consistent with the "Fed Information Effect" literature that predicts opposite signs for these effects (e.g. Romer and Romer, 2000; Campbell et al., 2012; Nakamura and Steinsson, 2018).

Although Bauer and Swanson (2023a) present substantial evidence against this strong Fed Information Effect story, our approach in this paper is much more direct. Here, we directly regress high-frequency, daily changes in market-implied expectations of macroeconomic variables on interest rate changes around monetary policy announcements, so we are able to exclude from our regressions all of the macroeconomic and financial confounding factors that Bauer and Swanson (2023a,b) argued were contaminating the monthly regressions studied by previous authors and driving the puzzling positive coefficients in their results. Our results highlight the efficacy of high-frequency data in clarifying the immediate impacts of monetary policy on macroeconomic forecasts, thereby contributing to a better understanding of the transmission channels of monetary policy.

The alignment of our results with standard macroeconomic models is particularly compelling, as it is derived from market-based expectations rather than researchers' interpretations of survey data. The direct nature of our testing approach obviates the need to control for omitted economic news, a common limitation of monthly-frequency analyses. By examining expectation changes in the immediate vicinity of monetary policy announcements, we provide a cleaner identification of policy effects than has been possible in most previous studies, allowing for a more definitive resolution of the ongoing debate on how monetary policy influences private-sector macroeconomic expectations.

All that said, we note that our results do not entirely rule out the possibility of a smaller "Fed Information Effect", or one that is significant only on a small number of isolated dates, as proposed by some previous authors (e.g., Jarocinski and Karadi, 2020; Lunsford, 2020). If that were the case, the Fed Information Effect could be small enough on average that we would still estimate significantly negative coefficients for the effects of monetary policy surprises on output, employment, and inflation. Our results only rule out the very large and ubiquitous information effects that have been proposed by the other authors cited above. A further investigation of whether a smaller Fed Information Effect does or does not exist would thus be an interesting avenue for future research.

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A Details of Kalshi Market-Implied Expectations Computation

This appendix describes how the daily Kalshi market-implied expectations of Section 2.3 are computed from the Kalshi data, and in particular how days and strikes with little or no trading are handled. Three layers are involved: which event-days enter the sample, which strikes enter the distribution on a given day, and what price is assigned to each strike.

Event-days. For each event (e.g., the August 2024 CPI release), we begin the daily series on the first day on which any contract for that event has traded, and we keep every subsequent trading day through expiration. A day with no trades in any of the event's contracts therefore remains in the sample once the event has started trading, with prices carried forward as described below; days before the first trade are excluded. Equivalently, an event-day observation is included whenever the cumulative trading volume of the event up to that day is positive.

Strikes. On a given day, the distribution is computed from the strikes for which the Kalshi daily feed contains a record that day, that is, a trade or a posted bid and ask. A strike with no record on that day is not part of that day's distribution, even if it traded on an earlier day. On liquid days this includes all listed strikes; on illiquid days it can be a small subset, and the subset can change from one day to the next. The trimming of the lowest and highest strikes described in Section 2.3 applies to this set: the two extreme strikes are excluded only when five or more strikes are recorded that day, so on thinly traded days nothing is trimmed.

Prices. For each included strike, the price p_{ths} is the last trade of the day if the strike traded that day, and otherwise the most recent earlier trade carried forward. If the strike has never traded, its price is the midpoint of the posted bid and ask quotes. The isotonic regression that enforces monotonicity across strikes (footnote 10) weights each strike by its cumulative trading volume, so that when a quote-only strike conflicts with traded prices it is effectively overridden by them; when the quotes are already monotone in the strike, which is the typical case, they enter the expectation at their quoted values. On a day on which only quote-only strikes are recorded, the implied expectation is computed from quotes alone, and when a single strike is recorded, the expectation is the midpoint of that strike's interval regardless of its price. Days on which no strike is recorded take the previous day's expectation.

The last two cases are rare for the federal funds rate, CPI, unemployment rate, and nonfarm payrolls contracts but occur for the longer-term GDP contracts in late 2022 and early 2023; Appendix C discusses their consequences.

B Summary Statistics of the Regression Samples

This appendix reports summary statistics for the samples used in the regressions. Appendix Table A1 describes the Federal Funds Rate contract sample of Table 3, and Appendix Table A2 the event-day sample of Tables 4, 5, and 6. The Internet Appendix reports the corresponding statistics for the expanded sample that includes quote-only event-days.

Appendix Table A1. Trading Volume Changes and Contract Maturity in the Federal Funds Rate Contract Sample

Summary statistics of the dependent variable and the maturity control in Table 3, for the full sample of Federal Funds Rate event-days and for the front, next, and longer-term contract groups used in its three columns. The dependent variable in Table 3 is the log of 1 plus daily trading volume, where an event's daily trading volume is measured as the one-day change in its cumulative contract volume; it is undefined on each event's first trading day, so the observation counts in Table 3 are slightly smaller than the group counts here. Sample: July 1, 2021 to December 31, 2025, event-days with positive cumulative volume.

	Mean	Std. dev.	P25	Median	P75
All events (N = 10,495)					
Daily trading volume	3,459.8	17,248.7	0.0	1.0	1,171.5
log(1 + daily volume)	3.467	3.779	0.000	0.693	7.067
Days to expiration	192.4	123.4	92.0	173.0	275.5
Front event (N = 1,581)					
Daily trading volume	15,925.8	40,472.9	112.5	3,433.0	12,894.5
log(1 + daily volume)	6.748	3.817	4.732	8.141	9.465
Days to expiration	36.1	16.2	24.0	36.0	48.0
Next event (N = 1,466)					
Daily trading volume	3,964.1	11,044.7	0.0	672.0	3,500.0
log(1 + daily volume)	5.291	3.616	0.000	6.512	8.161
Days to expiration	83.0	17.4	70.0	82.0	95.0
Longer-term events (N = 7,448)					
Daily trading volume	713.4	2,655.0	0.0	0.0	285.0
log(1 + daily volume)	2.411	3.226	0.000	0.000	5.656
Days to expiration	247.1	103.9	162.0	225.0	317.0

Appendix Table A2. Summary Statistics of the Event-Day Sample (Traded Events)

Event-day observations with positive cumulative trading volume, the sample of Tables 4, 5, and 6. "Front" refers to the event with the nearest release date and "Longer-term" to all later events. Announcement-day rows count the trading days in each column's sample on which the announcement occurred. Daily volume is the number of contracts traded. Sample: July 1, 2021 to December 31, 2025, except for Nonfarm Payrolls contracts, which begin in March 2023. The observation counts here equal those in Tables 5 and 6; the counts in Table 4 are slightly smaller because the daily volume change is undefined on each event's first trading day.

	CPI		Unemployment Rate		Nonfarm Payrolls		GDP	
	Front	Longer-term	Front	Longer-term	Front	Longer-term	Front	Longer-term
Observations	1,645	3,343	1,615	1,096	950	597	1,613	372
Unique events	55	52	54	43	33	37	19	14
Unique trading days	1,645	1,023	1,615	434	950	284	1,613	332
Events per day: mean	1.00	3.27	1.00	2.53	1.00	2.10	1.00	1.12
Events per day: std. dev.	0.00	2.90	0.00	1.68	0.00	2.00	0.00	0.33
Sample start	2021/07/01	2021/07/13	2021/07/04	2021/09/03	2023/03/10	2023/04/07	2021/07/01	2022/03/22
Sample end	2025/12/31	2025/11/12	2025/12/31	2025/12/16	2025/12/31	2025/12/31	2025/12/31	2025/07/30
FOMC announcement days	36	21	36	9	21	5	36	8
Fed Chair speech days	38	24	38	11	23	8	37	5
FOMC minutes days	37	22	36	10	22	8	36	7
Days to release: median	15	98	16	75	15	76	47	124
Days to release: min	0	28	0	24	0	24	0	90
Days to release: max	42	369	90	230	37	381	145	219
Daily volume: mean	123,827	3,714	26,928	2,503	80,048	19,633	117,985	1,359
Daily volume: min	99	1	1	3	25	1	172	10
Daily volume: max	2,000,239	676,989	484,961	122,073	1,375,561	895,983	2,110,113	147,103

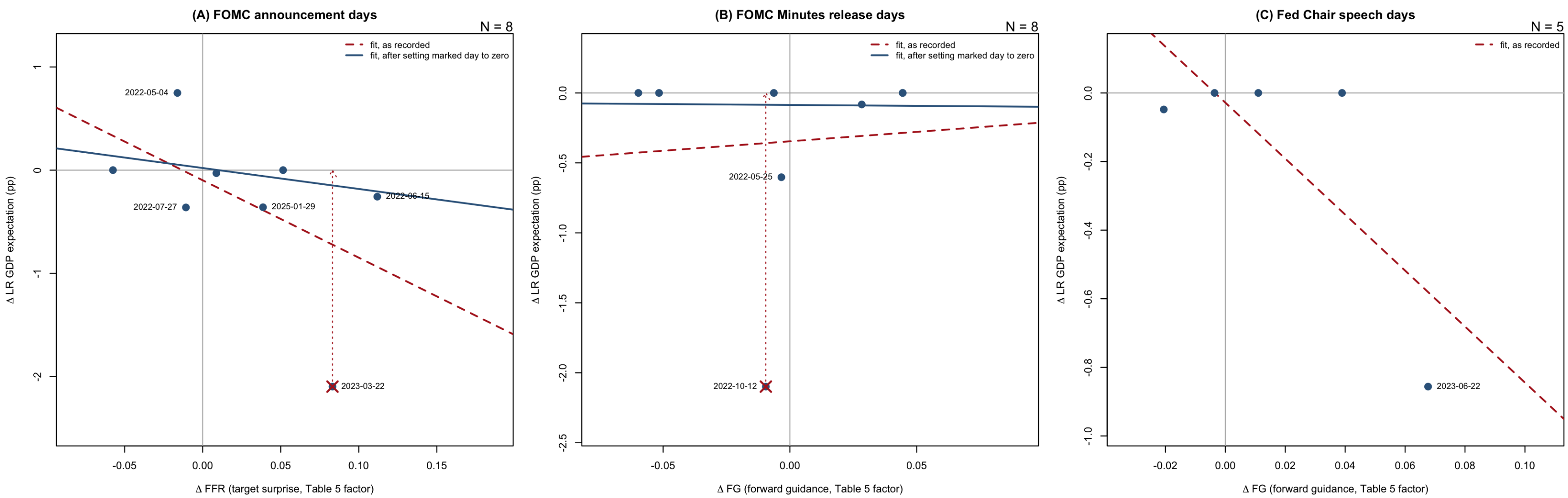
C Large Longer-Term GDP Contract Prices and Liquidity

In our analysis, the "front" contracts are those that are the closest to expiration, while "longer-term" (LT) contracts include all contracts with expiration later than that of the front contracts. However, note that GDP is only released once per quarter instead of once per month, so this means that the longer-term GDP contracts are at least a full three months away from expiration and thus can suffer from low liquidity as a result. In fact, the LT GDP contracts are generally the least liquid contracts in our data and have the smallest number of observations, especially in late 2022 and early 2023. This appendix discusses potential pricing issues for these LT GDP contracts related to their lower liquidity and how it relates to some of the coefficient estimates in Table 5.

Kalshi market-implied expectations for LT GDP contracts are computed as described in Section 2.3 and Appendix A. However, there are two Fed event days in our sample on which the change in the Kalshi market-implied LT GDP expectation was large but was not accompanied by any actual trades in those contracts after the announcement that day: the FOMC minutes release on October 12, 2022, and the FOMC announcement on March 22, 2023. On both days, the recorded change reflects the appearance or disappearance of posted quotes on strikes that had never traded rather than a change in traded prices. Because the implied expectations changes on these dates seem to be an artifact of low liquidity rather than a true change in market expectations, we treat the Kalshi market-implied expectations change on these two dates as zero; both days remain in the sample as zero-change observations.

A third date—the Fed Chair testimony on June 22, 2023—also has a large change in Kalshi market-implied LT GDP expectations, but on that date actual trades took place right after the testimony began, so we treat that data point as genuine.

Figure A1 plots the daily change in LT GDP expectations against the federal funds rate surprise on FOMC announcement days (Panel A) and against the forward guidance surprise on FOMC minutes release days (Panel B) and Fed Chair speech days (Panel C). The two observations set to zero are marked with a red "x" in Panels A and B, with dotted arrows showing where they move. The red dashed lines are the fitted bivariate regressions through the observations as recorded, and the blue solid lines the fitted regressions after the adjustment. In both panels, the marked observation lies far below all the others and accounts for the steep slope of the line as recorded. Panel C shows the June 22, 2023, observation, which we retain and which accounts for the large Fed Chair speech coefficient for LT GDP in Table 5.



Appendix Figure A1. Scatter Plots for Longer-Term GDP Contract Responses

Daily change in Kalshi market-implied LT GDP expectations on Fed event days against the Table 5 regressors: the FFR target surprise on FOMC announcement days (Panel A, $N = 8$), the forward guidance surprise on FOMC minutes release days (Panel B, $N = 8$) and the forward guidance surprise on Fed Chair speech days (Panel C, $N = 5$). Red crosses mark the two Fed-event-day observations set to zero (March 22, 2023, in Panel A; October 12, 2022, in Panel B); dotted arrows show where they move. Red dashed lines: bivariate fit as recorded; blue solid lines: fit after the adjustment. These bivariate slopes differ from the multivariate slope coefficients in Table 5. Sample: July 1, 2021 to December 31, 2025 (the first longer-term GDP observation is on March 22, 2022).

Setting these observations to zero only affects the LT GDP column of Table 5, and it is conservative. Without the adjustment, the FFR Target Surprise coefficient would have been even larger, -10.11 (s.e. 5.13), instead of -5.22 (3.08), and the Forward Guidance $\times$ FOMC Minutes coefficient would have been 2.06 (2.31) instead of 0.87 (1.07); March 22, 2023, accounts for the former and October 12, 2022, for the latter. Conversely, had we also set June 22, 2023, to zero, the coefficient on Fed Chair Speeches in Table 5 would have fallen from -8.95 (3.82) to -0.27 (0.65); that cell rests on five Chair-speech observations and this one drives it, which is why we report it but do not emphasize it. The pooled results in Table 6 are essentially unchanged by any of these choices: without the adjustment the longer-term target coefficient is -12.10 rather than -11.66, and it is -11.79 if LT GDP is dropped altogether.

D Pooled Regression Weights

Appendix Table A3 reports the sensitivity regressions (6) behind the weights $\omega^{m,h}$ and ω^{m} of equation (7) used in Table 6.

Appendix Table A3. Average Sensitivity of Contract-Implied Macro Expectations to Interest Rate Changes and Pooled Regression Weights

OLS estimates of regression (6): the standardized daily change in the market-implied expectation for each event, by macro series and horizon, regressed on the daily changes in the near-term (FF2) and longer-term (SOFR4) futures rates, with no fixed effects. Standard errors (in parentheses) are two-way clustered by trading day and event (contract expiration month). $\overline{\beta}^{m,h}$ is the average of the two sensitivities and $\omega^{m,h} = 1/|\overline{\beta}^{m,h}|$, normalized to sum to 100% within each horizon, is the weight used in columns 2 and 3 of Table 6; $\overline{\beta}^{m}$ averages $\overline{\beta}^{m,h}$ across the two horizons and $\omega^{m} = 1/|\overline{\beta}^{m}|$, normalized across series, is the weight used in column 1. Sample for these weight regressions: December 27, 2021 to December 31, 2025 (Nonfarm Payrolls from March 2023), traded contract-days only; the weights are held fixed at these estimates in Table 6, whose sample begins July 1, 2021. Significance levels: $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$. Bold denotes significance at the 10% level or better.

		Sensitivity to		By horizon		All horizons			
Macro Series	**Horizon**	FF2	SOFR4	$\overline{\beta}^{m,h}$	$\omega^{m,h}$	$\overline{\beta}^{m}$	ω^{m}	N	Adj. R^2
CPI	Front	0.454	0.002	0.228	19.0%	0.164	40.8%	1,466	−0.001
		(0.357)	(0.222)						
	Longer-term	0.345	−0.144	0.100	61.7%			3,238	0.000
		(0.246)	(0.147)						
Unemployment	Front	−0.019	−0.185	−0.102	42.5%	0.338	19.8%	1,442	−0.001
		(0.271)	(0.197)						
	Longer-term	**1.322*****	−0.174	0.574	10.8%			1,094	0.001
		(0.411)	(0.289)						
Payrolls	Front	1.468	−0.578	0.445	9.7%	0.875	7.7%	950	0.000
		(1.561)	(0.385)						
	Longer-term	2.222	0.387	1.305	4.8%			597	−0.001
		(1.942)	(0.718)						
GDP	Front	−0.145	**0.447****	0.151	28.7%	0.212	31.7%	1,441	0.000
		(0.175)	(0.185)						
	Longer-term	0.252	0.293	0.272	22.7%			372	−0.004
		(0.407)	(0.447)						