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Kalshi and the Rise of Macro Markets

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Abstract

Prediction markets offer a new market-based approach to measuring macroeconomic expectations in real-time. We evaluate the accuracy of prediction market-implied forecasts from Kalshi, the largest federally regulated prediction market overseen by the CFTC. We compare Kalshi with more traditional survey and market-implied forecasts, examine how expectations respond to macroeconomic and financial news, and how policy signals are interpreted by market participants. Our results suggest that Kalshi markets provide a high-frequency, continuously updated, distributionally rich benchmark that is valuable to both researchers and policymakers.

JEL Codes: E3, G1, C5.

Keywords: Kalshi, Federal Reserve, prediction markets, expectations, forecasting

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1 Introduction

Managing expectations is central to modern macroeconomic policy. Yet the tools that are often relied upon—surveys and financial derivatives—have many drawbacks. Surveys can quickly become stale and ask specific questions that often provide point forecasts without any measure of uncertainty. Financial derivatives are also limited to certain contracts and trading may be thin. This paper introduces a new source of real-time, financially-backed expectations data: Kalshi macroeconomic prediction markets. Kalshi is the first federally regulated platform where traders bet directly on economic outcomes such as inflation, payrolls, and Federal Reserve decisions. Using high-frequency trading data, we show that these markets yield well-calibrated, rapidly updating density forecasts on important economic variables, including several for which alternatives are not available. Our study highlights the promise of prediction markets as a new benchmark for measuring expectations and informing monetary policy decisions.

Despite a large literature using surveys, options, and asset prices to infer macroeconomic expectations (e.g., [Gürkaynak, Sack and Swanson \(2012\)](#), [Nakamura and Steinsson \(2018\)](#), [Swanson \(2021\)](#)), real-money prediction markets remain underexplored within macro-finance. This reflects the shortcomings of earlier platforms, which were often thin, unregulated, or focused on non-economic outcomes. The availability of credible, liquid markets for macro variables now enables a direct, incentive-compatible lens on expectations—one that avoids many of the limitations of existing proxies. Our analysis is one of the first to systematically examine this new data source.

Kalshi, the largest CFTC-approved prediction market in the United States, began operating in 2021. Classified as a “Designated Contract Market”—the same category as the Chicago Mercantile Exchange—it is supported by market makers such as Susquehanna. Kalshi contracts are also accessible to retail traders through brokerage platforms like Robinhood and Webull. Each contract is a simple Arrow-Debreu security that pays one dollar if the specified outcome occurs; therefore, the full risk-neutral probability density function (pdf) of an event can be constructed by the set of contracts in the given market. Kalshi provides intradaily trade data for different measures of CPI (MoM, YoY, or calendar year), Core CPI, PCE inflation, unemployment rate, payroll releases, GDP growth, probability of recession, and federal funds rate target rates meeting-by-meeting. Several of these are variables for which there were no previous financial derivatives trading.

We begin by showing that the probability distributions implied by Kalshi markets are well-behaved and broadly consistent with those from more established financial instruments. We find that in several episodes, they allocate probability mass in ways that may reflect the

range of plausible macroeconomic outcomes better than traditional financial derivative or survey-based forecasts.

Second, we document rich intraday dynamics in Kalshi markets. These probabilities respond sharply and sensibly to major developments. For example, the implied probability of a rate cut at the July 2025 FOMC rose to 25% following remarks from Governors Waller and Bowman, before falling after a stronger-than-expected June employment report. This pattern is representative of the broader high-frequency responsiveness we observe and is missed with daily data.

Third, we evaluate the forecasting performance of Kalshi markets relative to the Survey of Market Expectations run by the Federal Reserve Bank of New York (FRBNY). For the federal funds rate forecasts 150 days (3 FOMC meetings) ahead, Kalshi's mean absolute error is very similar to that of professional forecasters. But unlike the survey—which provides a snapshot every six weeks of a modal path—Kalshi offers a continuously updating full distribution. We provide a preview of these results in Figure 1. This figure shows the mean absolute prediction error, averaging across all FOMC meetings, plotted against the number of days before the FOMC meeting. We find the Kalshi median and mode have a perfect forecast record on the day before the FOMC meeting, which represents a statistically significant improvement over the fed funds futures forecast.

We also assess CPI and unemployment forecasts relative to the Bloomberg consensus. We find that Kalshi expectations are statistically similar for core CPI and unemployment, with forecast errors that are almost the same as the Bloomberg consensus. In contrast, for headline CPI, we find Kalshi provides a statistically significant improvement over the Bloomberg consensus forecast.

Fourth, we demonstrate that Kalshi provides real-time, distributional forecasts for macroeconomic variables such as GDP, core CPI, and unemployment—markets for which options data have historically been unavailable. While option-implied distributions exist for equities, interest rates, and CPI headline inflation swaps, Kalshi uniquely extends this to other headline macro indicators at high frequency while providing a more retail-investor perspective. Moreover, there are no currently trading options that give distributions of the federal funds rate after specific FOMC meetings, another hole that Kalshi fills.

Fifth, with access to full distributions, we uncover new patterns in how macroeconomic news affects the moments of the Federal Funds rate distribution. We study how different kinds of news announcements affect the mean, variance and skewness of interest rate beliefs. We find that, during the 2022-2025 period, the variance of interest rate distributions declines substantially following data announcements, especially inflation releases. We split out the announcements of CPI inflation into ones which were positive surprises, negative surprises

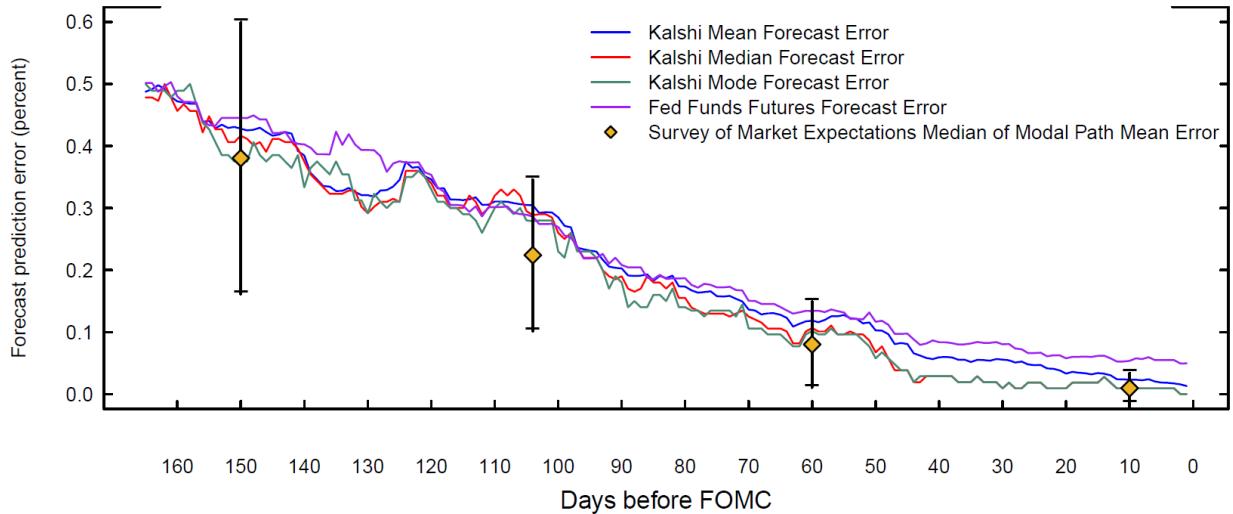


Figure 1: **FOMC Federal Funds Rate Forecast Errors Comparison**

This figure compares the mean absolute errors from 160 days out to each FOMC for the effective federal funds rate since 2022. The vertical bars reflect one-half standard deviation for the forecast errors for the Survey of Market Expectations and correspond to when the surveys were completed.

and zero surprises. We find that the variance of interest rates declines the most following a zero surprise inflation release, but also falls—though to a lesser extent—after both positive and negative surprises, consistent with a general resolution of uncertainty. Furthermore, we uncover an asymmetry with respect to the first moment, where positive shocks to CPI lead to much larger responses in the mean of the fed funds rate when compared to negative CPI shocks. We also examine the effects of macro surprises on the moments of the Federal Funds rate in a standard event-study regression and find many of these moves are statistically significant.

Lastly, we conduct event study regressions for the effects of monetary policy shocks on the distribution of the Federal Funds rate. We find that shocks associated with the release of the FOMC statement have statistically significant impacts on not just the first moment, but also tend to increase the second moment. In contrast, shocks associated with the press conference have limited effect on the first moment but a significant and negative effect on skewness, implying some potential resolution of upside uncertainty to interest rates during this window.

We intend (subject to approval) to make the distributional daily-level data publicly available via an interactive website at EconFutures.com, offering downloadable time series and visualizations for each contract, as well as trade-level data and code to further update prediction market data available on [this paper's GitHub](#). Our goal is to facilitate further research and enable policymakers to easily monitor shifts in investors' beliefs in real-time.

Our paper touches upon several strands of the macro-finance literature. A large body of work extracts interest rate beliefs from options prices. Seminal contributions include [Aït-Sahalia \(1996\)](#), who develops nonparametric pricing methods, and [Ball and Torous \(1999\)](#), who highlight the role of stochastic volatility. Subsequent research emphasizes unspanned volatility ([Fan, Gupta and Ritchken, 2003](#); [Li and Zhao, 2006](#)) and the pricing implications of volatility smiles ([Jarrow, Li and Zhao, 2007](#); [Amin and Ng, 1997](#)). Other studies examine the structure of state price densities ([Bakshi and Madan, 2000](#); [Li and Zhao, 2009](#)) and the pricing of caps and swaptions ([Longstaff, Santa-Clara and Schwartz, 2001](#); [Miltersen, Sandmann and Sondermann, 1997](#)), while more recent work by [Mertens and Williams \(2021\)](#) uses option prices to derive expectations related to the zero lower bound and [Wright \(2018\)](#) evaluates options for longer-maturity real interest rates. Although informative, many of these approaches rely on complex structural models that infer expectations from instruments indirectly related to the policy rate. In contrast, we use prediction market data explicitly tied to the federal funds rate and other macroeconomic variables, enabling the recovery of risk-neutral probabilities with minimal assumptions at high frequency.

Our work is also closely related to studies of monetary policy expectations, uncertainty, and skewness. [Gürkaynak, Sack and Swanson \(2012\)](#) construct measures of market-based policy expectations, while [Beber and Brandt \(2006\)](#) show that macroeconomic news affects both beliefs and preferences as reflected in options markets. More recent work explores the role of monetary policy uncertainty ([Bauer, Lakdawala and Mueller, 2022](#); [Wright, forthcoming](#)) and the pricing of asymmetric policy responses—often labeled the “Fed put” ([Cieslak and Vissing-Jorgensen, 2021](#)). Our analysis contributes to this literature by introducing a high-frequency, event-level measure of policy expectations distributions from prediction markets. We show that macroeconomic news significantly shifts not only the mean but also higher moments of the federal funds rate distribution in asymmetric ways. Asymmetries in interest rate distributions have also been explored for longer-dated yields as in [Bauer and Chernov \(2024\)](#), while [Diercks, Tanaka and Cordova \(2024\)](#) focus on skewness in expectations of interest rates coming from the FRBNY’s Survey of Primary Dealers.

A related literature examines beliefs about inflation extracted from options markets. [Kitsul and Wright \(2013\)](#) provide an early and influential analysis of risk-neutral inflation density functions, measuring risk of high inflation and deflation, and documenting meaningful variation in higher moments around key macroeconomic events. [Fleckenstein, Longstaff and Lustig \(2017\)](#) use inflation options to quantify market-implied deflation risk, while [Hilscher, Raviv and Reis \(2022\)](#) and [Hilscher, Raviv and Reis \(2024\)](#) explore how the pricing of extreme inflation outcomes informs debates on debt sustainability and macroeconomic fragility. [Rich and Tracy \(2010\)](#) compare market-based and survey-based measures, highlighting differences

in expectations, disagreement, and uncertainty. Our analysis contributes to this literature by introducing a new source of market-based inflation expectations—derived from prediction markets—which provides direct, high-frequency measures beliefs about upcoming releases of both headline and core inflation. Whereas the existing inflation swaps and options reference headline inflation over periods of a year or more, Kalshi is different in giving information about upcoming data announcements, and also including information about core inflation.

Also related to our work is a growing literature that highlights the informational value of retail investor behavior. While early research often emphasized behavioral biases, recent studies show that retail trading can enhance market efficiency. [Farrell, Green, Jame and Markov \(2022\)](#) find that the rise of retail trading has increased the informativeness of prices, particularly around earnings announcements. [Boehmer, Jones, Zhang and Zhang \(2020\)](#) show that retail order flow predicts returns, and [Kelley and Tetlock \(2013\)](#) find that aggregated retail trades reflect valuable firm-level information. [Kelley and Tetlock \(2017\)](#) further show that retail short-selling contains predictive content for future stock price movements. [Chen, De, Hu and Hwang \(2014\)](#) also demonstrates that retail opinions shared via social media platforms contribute meaningfully to price discovery. Our use of prediction market data offers a new lens on retail investor expectations, capturing their beliefs directly and in real time, independent of the portfolio constraints and hedging motives that can often shape the positions of institutional investors, potentially generating sizeable risk premiums.

More broadly, we contribute to the forecasting literature that assesses the informativeness of financial market instruments and surveys, along with their distributions ([Ang, Bekaert and Wei, 2007](#); [Bakshi, Panayotov and Skoulakis, 2011](#); [Christoffersen, Jacobs and Chang, 2013](#); [Clements, 2018](#); [Goff, Kostka and Masera, 2014](#); [Duffee, 2012](#); [Wright and Faust, 2012](#)). We show that prediction market forecasts are an improvement over fed funds futures and perform as well as those from the Survey of Market Expectations (SME) conducted by the FRBNY. We also show that prediction market-based inflation forecasts have been roughly comparable to the Bloomberg consensus, while updating more frequently.

Lastly, and most importantly, our work builds on a substantial literature examining prediction markets and economic forecasting. [Snowberg, Wolfers and Zitzewitz \(2013\)](#) and [Wolfers and Zitzewitz \(2004\)](#) provide comprehensive reviews of prediction markets in this context. The study closest to ours is [Gürkaynak and Wolfers \(2005\)](#), which analyzed the now-defunct Economics Derivatives market developed by Goldman Sachs and Deutsche Bank. [Hanson and Oprea \(2009\)](#) shows that even in the presence of manipulation, prediction markets can yield reliable forecasts, and [Snowberg and Wolfers \(2010\)](#) examine behavioral biases that may affect pricing. Our contribution builds on this literature by applying prediction markets to the study of monetary policy, inflation, and other macro expectations using newly

available contracts with high-frequency, event-level granularity.

We also acknowledge several concurrent studies that complement our findings. [Swanson, Wang and Wu \(2025\)](#) use Kalshi data to evaluate the Fed information effect, confirming that monetary policy shocks reduce expectations for both growth and inflation. [Burgi, Deng and Whelan \(2025\)](#) examine the full range of Kalshi markets and find them to be valuable forecasters for nearly all events, many of which are unrelated to economic variables. [Eichen-green, Viswanath-Natraj, Wang and Wang \(2025\)](#) use Polymarket data to explore questions surrounding Fed independence. We complement these contributions by focusing on extensively validating Kalshi as a forecasting tool and as a source of market-based expectations for key macroeconomic variables that are at the core of the Federal Reserve’s mission, while also documenting real-time stagflationary risks and asymmetric responses of fed funds rate distributions to news surprises. In addition, we provide codes and a transparent process for constructing probability distributions from underlying prediction market trades, facilitating future use by both researchers and policymakers.

Our paper is structured as follows. Section 2 reviews institutional details of prediction markets. Section 3 documents how we convert Kalshi options prices to probability distributions. Sections 4 and 5 compare the Kalshi point and density forecasts with alternatives around specific episodes. Section 6 gives a comparison of forecasts by average absolute error. Section 7 examines how Kalshi predictions respond to news announcements, and section 8 concludes.

2 Institutional Features and Design of Kalshi Markets

2.1 Overview

Prediction markets are financial platforms where users can trade contracts that pay out based on the outcome of real-world events, such as elections, sporting events, or macroeconomic releases. These contracts function similarly to options. A trader can buy or sell an option for a price x that pays off \$1 if a given outcome occurs and nothing otherwise. The exchange naturally takes no position, and so every option has to have a buyer and a seller.

Kalshi, the largest CFTC-approved prediction market, defines a market as a single binary contract (e.g., ”CPI exceeds 2.5% YoY in March 2025”), and a series as a group of related markets (e.g., CPI exceeding various thresholds across different months). Kalshi has gained significant traction, with market making provided by firms such as Susquehanna. Retail investors can access Kalshi contracts via platforms like Robinhood and Webull. This growing infrastructure makes prediction markets a viable and valuable subject for economic study.

Competing Platforms. Other platforms offering prediction markets include Polymarket, PredictIt, and Interactive Brokers. Of these, only Kalshi and Interactive Brokers operate under regulatory approval. Polymarket operates in a legal gray area and, along with PredictIt and Interactive Brokers, supports fewer contracts, lower liquidity, and smaller individual position limits. Kalshi’s maximum exposure per market currently reaches \$7 million.

Given these distinctions, we argue that Kalshi represents the most mature and comprehensive prediction market for economic forecasting. Accordingly, we rely on Kalshi data for the remainder of this paper.

Forecast Markets on Macroeconomic and Monetary Policy Events. We identify a promising new class of prediction markets focused specifically on macroeconomic indicators and monetary policy outcomes. Table 1 lists several key Kalshi series in this space, including CPI, payroll releases, and FOMC decisions—events that typically attract substantial attention from financial markets.

Series	First Contract	Frequency	Theme
CPI MoM	June 2021	Monthly	Inflation
CPI YoY	November 2022	Monthly	Inflation
CPI for Year	2022	Annual	Inflation
Core CPI MoM	June 2022	Monthly	Inflation
Core CPI YoY	December 2022	Monthly	Inflation
Core CPI for Year	2025	Annual	Inflation
Unemployment Rate	July 2021	Monthly	Labor Market
Payroll Release	March 2023	Monthly	Labor Market
GDP Growth	Q2 2021	Quarterly	Growth
GDP Growth	2025	Annually	Growth
Probability of US Recession	2022	Annually	Growth
Federal Funds Rate Decision	May 2023	FOMC	Monetary Policy
Federal Funds Rate Target Rate	December 2021	FOMC	Monetary Policy

Table 1: **Kalshi Markets of Interest**

There are thousands of Kalshi markets available, but we deem these particular markets to be the most economically relevant.

Prior literature has shown that surprises in these events can significantly move asset prices, elevate market volatility, and contribute to macroeconomic uncertainty. Since central bank decisions depend heavily on incoming data and market expectations, accurate, real-time forecasting of these variables is vital for effective policy implementation.

Why High-Frequency Forecasts Matter. Prediction markets offer high-frequency, continuously updating forecasts that can complement central bank decision-making. High-frequency data let us apply an event study methodology to see how news shapes beliefs

about macroeconomic indicators. For macroeconomic indicators like CPI and unemployment—two pillars of the Federal Reserve’s dual mandate—market-based forecasts improve the Fed’s ability to communicate policy direction and assess the market’s perceived reaction function under various scenarios.

For monetary policy itself, such as upcoming FOMC decisions, prediction markets offer a valuable check on the effectiveness of Fed communication. Importantly, these markets can also reflect the entire distribution of expectations, helping policymakers understand tail risks, asymmetries, and market uncertainty—information that is lost when only modal or median expectations are provided.

2.2 Traditional Forecasting Approaches

Table 2 summarizes commonly used forecasting tools for the economic indicators listed in Table 1. These tools fall into two categories: surveys and market-based measures.

2.2.1 Survey-Based Forecasts

Surveys offer forecasts without requiring complex models or assumptions and are not subject to risk premia since respondents do not face financial consequences for their predictions. Notable surveys include:

- **Survey of Market Expectations** (SME) by the Federal Reserve Bank of New York (formerly SPD/SMP), which elicits expectations for upcoming FOMC decisions and some year-end macroeconomic variables.
- **Bloomberg Consensus**, which collects modal expectations for macroeconomic announcements shortly before they are released.
- **Blue Chip Economic Indicators**, which gather monthly modal expectations for year-end GDP and CPI.

While surveys have been considered rather accurate on average ([Ang, Bekaert and Wei, 2007](#)), they are generally infrequently available and may not reflect updates in real-time. Also, numerous studies have rejected the full information rational expectations hypothesis in survey expectations. Anchoring, inertia, and reputational concerns can distort survey results (see [Diercks and Jendoubi \(2023\)](#) for further discussion).

Source	Variables	Horizon	Frequency	Type	Format
Bloomberg Consensus Survey	CPI/Payrolls/GDP releases & Fed decisions	Next release	Once-per-event	Survey	Point-estimates
Survey of Market Expectations PDFs	Fed decisions & EoY CPI, GDP	2 FOMC Meetings	Once-per FOMC cycle	Survey	Distribution
Survey of Market Expectations Paths	Fed decisions	6 FOMC Meetings	Once-per FOMC cycle	Survey	Point-estimates
Blue Chip Economic Indicators	GDP/PCE/ Unemployment	Quarterly 2-Years ahead	Once-per-month	Survey	Point-estimates
Survey of Professional Forecasters	GDP/CPI/ Unemployment	Annual 2-Years ahead	Once-per-quarter	Survey	Distribution
Federal Funds Rate Futures ¹	Fed decisions	Far	Market-based	Market-based	Point-estimates
SOFR options	Fed decisions	Far	Market-based	Market-based	Distribution
Overnight Interest Rate Swaps	Fed decisions	Far	Market-based	Market-based	Point-estimates
CPI Fixings	CPI releases	One year before	Market-based	Market-based	Point-estimates
Kalshi	CPI/Payrolls/GDP releases & Fed decisions	Next release & Next 4 FOMC meetings	Market-based	Market-based	Distribution

Table 2: **Forecast Tools**

This table shows the available forecast tools along with the relevant variables, the horizons, how frequently they are available, and whether or not they provide only point estimates or full distributions.

2.2.2 Market-Based Forecasts

Market-based measures offer the advantage of near-instantaneous updating in response to news. For monetary policy, key instruments include:

- **SOFR Options**, which provide liquid estimates of the distribution of SOFR over quarterly horizons. However, while SOFR futures are one of the most heavily traded interest rate derivatives, their options are much less traded. Moreover, these are options on one-month or three-month average repo rates. Translating these into forecasts for specific FOMC meetings requires strong and unreasonable assumptions. Moreover, the basis between SOFR and the effective federal funds rate can be time-varying and, at times, substantial.
- **Federal Funds Futures**, which offer mean rate forecasts by calendar month. Unfortunately, they do not give the entire distribution of outcomes, unless one is willing to assume that there are only two possible outcomes, which can be problematic in times of high uncertainty or when looking beyond the next meeting. While there was a time when Fed Funds futures options were traded (see [Emmons, Lakdawala and Neely \(2006\)](#)), this came to a halt following the financial crisis back in 2008.

Overall, we argue that Kalshi should be used to provide risk-neutral pdfs concerning FOMC decisions at specific meetings because SOFR is too far removed from the monetary policy interest rate decision (both because of the basis and the different time horizon) and these are the only other short-term interest rate options that actually trade.

For inflation, **CPI Fixings** provide mean expectations for specific releases but are primarily institutional products with limited retail accessibility. More broadly, most of the markets described above are dominated by large institutions that use them primarily for hedging purposes. Outside of prediction markets, we are unaware of any market-based forecasts for other important upcoming releases such as payrolls, unemployment, GDP, or core CPI. There are also inflation swaps and options, but these have much longer maturities (see [Diercks, Campbell, Sharpe and Soques \(2023\)](#) for analysis of the relative forecast performance of inflation swaps).

2.3 Volume

Given that Kalshi is relatively new when compared to more established markets such as Fed Funds futures, it is natural to wonder about its liquidity. Liquidity is important as it helps to ensure prices reflect real-time information from incoming news. As noted above, in recent

years, quotes on options for Fed Funds futures have been provided on an indicative basis, but are not actually traded.

In contrast, Kalshi contracts for the federal funds rate have relatively large liquidity. Figure 2 shows a volume heatmap for every contract dating back to 2021 for the federal funds rate. In this figure, the darker the shading, the greater the volume. One can see that recent periods have had volumes greater than a million for several strikes.

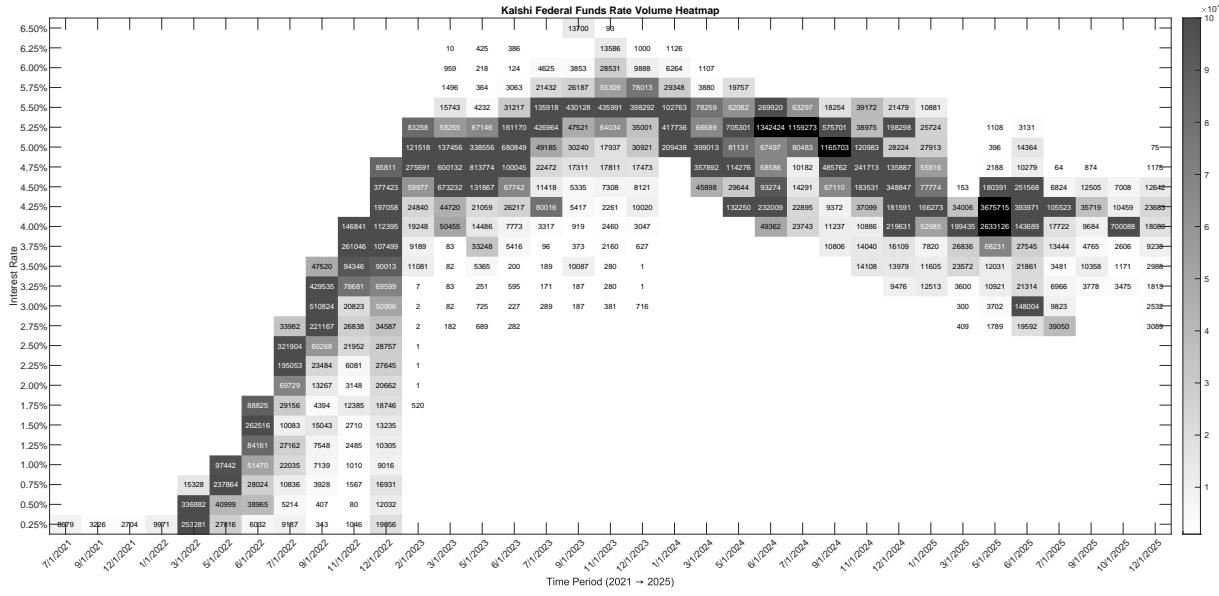


Figure 2: Volume Heatmap for Kalshi Federal Funds Rate Forecasts

This chart shows the volume for each strike price for each meeting as of June 2025. Each box is shaded based on the level of volume, with darker boxes corresponding to greater volume.

The volume over time has been growing in this market. Figure 3 shows that the volume has been frequently above a million in recent years, with the peak recently reaching close to 100 million in volume for the September FOMC. These volumes compare favorably to SOFR options, as well.

3 Converting Kalshi into Probability Distributions

Kalshi structures financial and macroeconomic contracts as a series of binary options that pay \$1 if the realized outcome exceeds a specified strike. Figure 4 illustrates this structure for the December 2025 FOMC meeting. Each contract allows users to trade “Yes” or “No” positions, depending on whether they believe the event will occur. Our objective is to convert the market prices of these binary contracts into an implied probability distribution, updated daily, to produce high-frequency forecasts for key macroeconomic variables.

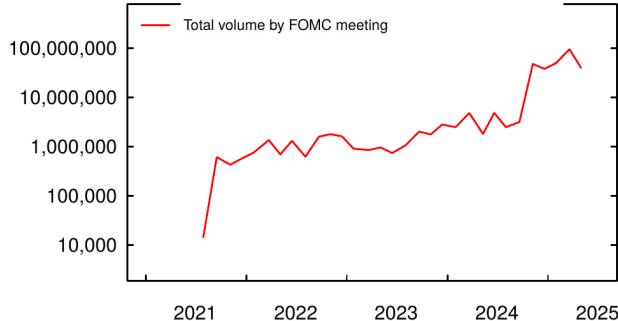


Figure 3: **Volume Time Series for Kalshi Federal Funds Rate Markets (Log Scale)**

The chart shows the total volume for each FOMC meeting based on the log scale dating back to 2021. These values reflect the sum of the markets for the Federal Funds Rate Decision and the Federal Funds Target Rate.

Methodology. We begin by scraping trade-level data from Kalshi. We then apply a straightforward mapping from market prices to probability mass, treating the price of a “Yes” contract as the market-implied risk-neutral probability that the event occurs. In contracts that cash as long as the outcome exceeds the strike (rather than the outcome falling in a specific bin), we calculate the probability of the outcome by subtracting from the “Yes” price of exceeding the previous strike. For instance, in Figure 4, the 4.0 strike has a last-traded price of \$0.40, while the 4.25 strike has a last-traded price of \$0.22, so we calculate an 18% probability the Fed Funds rate falls between 4.0 and 4.25².

In the event a strike has no traded contracts on a day, we carry over the last-traded strike from a previous day. Sometimes, two strikes have the same price³, and in that case we assign the probability to the outcome closer to the mode. This simple, model-free approach allows us to construct a daily-updating risk-neutral pdf over the relevant outcome space. Once we have the risk-neutral pdf, we can immediately work out the implied moments, notably the mean. In subsequent sections, we demonstrate that this parsimonious approach improves forecast performance and enhances analytical flexibility over existing forecast tools.

Caveats and Discussion. While our approach is straightforward, there are some caveats worth noting. First, as with all options, it is giving risk-neutral probabilities under the **Q** measure, not actual physical probabilities under the **P** measure. In other words, the probabilities may be distorted by risk premia. The retail investor base of Kalshi might alter the risk premia properties. We will return to assessing the risk premia later. Separately, the outermost (tail) contracts often suffer from low trading volume, which can lead to stale prices

²Kalshi’s contract is denoted for the upper bound of the FFR, so in practice the probability allocated between 4.0 and 4.25 being 18% implies a 18% chance on the target range being 4.0-4.25.

³This happens mostly near the tails, since prices are bounded between \$0.01 and \$0.99.

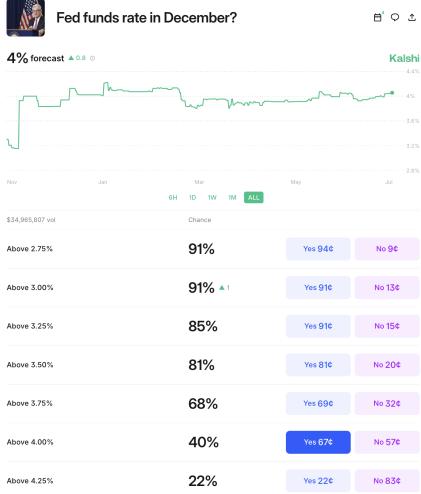


Figure 4: **Fed Funds Rate for December 2025 contract**

The prices shown in this figure were captured on July 22, 2025. The underlying contract is for determining the federal funds rate in December. In this market, the upper bound of the range is considered when evaluating the outcome. The “Above 4.25” outcome corresponds to the target range or no further rate cuts by December 2025, as of the time the image was captured.

and noisy estimates in the tails of the distribution—especially in illiquid markets. However, these issues are not unique to Kalshi. SOFR options also suffer from sparse trading in extreme outcomes and Fed Funds Futures options over the past several years have not traded at all. To mitigate tail-related distortions, we enforce monotonicity in the CDF by constructing the distribution outward from the mode toward the tails. This approach prevents stale or illiquid pricing in the tails from contaminating the rest of the pdf. We find that enforcing monotonicity of our cdf starting from the mode improves the reliability when compared to starting on one side or the other when constructing the distributions. We highlight that constructing complete distributions from Kalshi’s economic contracts can have challenges, and we intend to make public complete code packages which do so from trade-level and bid-ask data.

Even with these limitations, the probability distributions implied by Kalshi prices compare favorably to these alternative market-based forecasts when evaluated on predictive accuracy. While refinements—such as inferring probabilities from the midpoint of bid-ask spreads—may further improve precision, we find such enhancements are not necessary to deliver forecasting gains.⁴ More importantly, Kalshi provides the fastest-updating distributions currently available for many key macroeconomic indicators, and the only reasonable

⁴We find that midpoints of bid-ask spreads seem to introduce additional issues due to occasionally large spreads on tail outcomes. See the Appendix for more discussion.

distributions available for macroeconomic indicators like GDP, Unemployment, or Core CPI. It is also the only financial option with active trading which directly gives beliefs about the Federal Funds rate.

4 Time-Series Comparisons to Existing Benchmarks

A natural question is how the time-series evolution of Kalshi-implied forecasts compares to established benchmarks. In this section, we document both the similarities and differences between Kalshi and more traditional market-based measures, such as Federal Funds futures and overnight index swap (OIS) rates.

Federal Funds Rate Projections. Figure 5, left panel, displays the evolution of federal funds rate expectations following the December 2024 FOMC meeting. The Kalshi-implied mean forecast (red line) closely tracks both market-based expectations and the consensus from the Survey of Market Expectations. Notably, the sharp decline in forecasts at the end of July—following the FOMC’s signal of a likely rate cut in September—is more pronounced in the OIS and fed funds futures data. In contrast, the Kalshi mean and the SME consensus exhibit a more gradual adjustment, with broadly similar timing and magnitude.

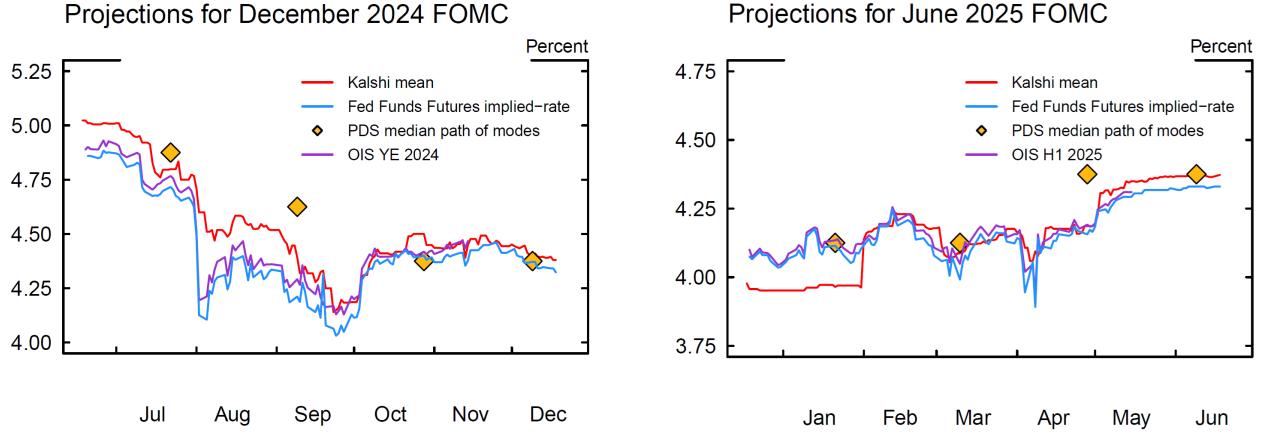


Figure 5: FOMC Federal Funds Rate Comparisons

The chart on the left shows the federal funds rate projections for the period following the December 2024 FOMC meeting. OIS YE 2024 corresponds to the overnight index swap rate for the end of 2024. The PDS Median path of modes corresponds to the Survey of Market Expectations median of modal path projection for the federal funds rate. The chart on the right shows similar projections for the June 2025 FOMC meeting.

In the right panel, we see that the projections for June 2025 FOMC are also fairly similar across the different approaches. One slight difference is that the Kalshi mean did not decline

as much in early April, which ended up being prescient given the developments that unfolded during that period.

Federal Funds Rate Intermeeting Period Dynamics. We can also more closely track the time series of probabilities for particular rate outcomes for a given meeting. For instance, in Figure 6, we plot the time series of the probability of the most likely rate outcome for the July 2025 FOMC (blue line). For July 2025, this corresponds to the probability of no rate change. One can see that the probability of no rate change declined following several communications that were interpreted by investors as more accommodative than expected. This led the probability to fall below 80%. It wasn't until the June Nonfarm Payrolls report that the probability of no rate change jumped above 90%.

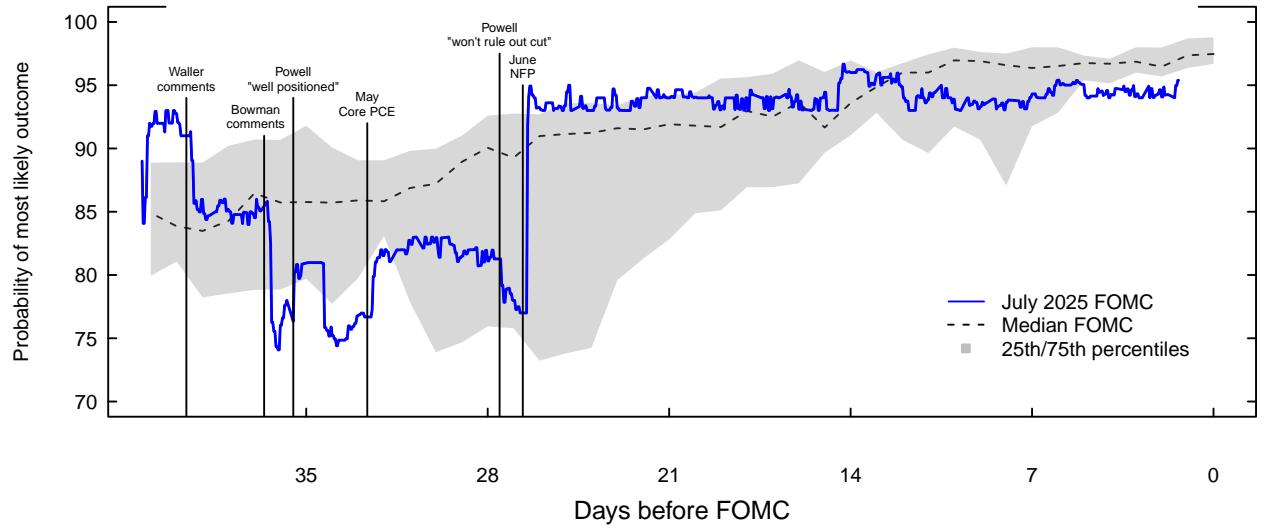


Figure 6: Probability of Most Likely Rate Outcome Before July 2025 FOMC

The chart shows the probability of the most likely outcome for the July 2025 FOMC (blue line), in this case for no rate change. The rest of the historical distribution in terms of the 25th to 75th percentile is shown in gray, with the dashed black line reflecting the median.

CPI Inflation Projections. Kalshi also provides mean forecasts for CPI. The chart on the left of Figure 7 shows that the May 2025 CPI had been drifting down following the release of the April 2025 CPI which came in lower than expected, as shown by the right panel. This chart demonstrates that both the Bloomberg consensus and the Kalshi-implied mean can at times line up closely. However, a key difference is that Bloomberg consensus has no time series and is only available in the months before a release. For instance, we learn that developments around early April caused a spike in expectations for inflation, but

this did not persist. The evolution of these dynamics are not possible to observe for the Bloomberg Consensus.

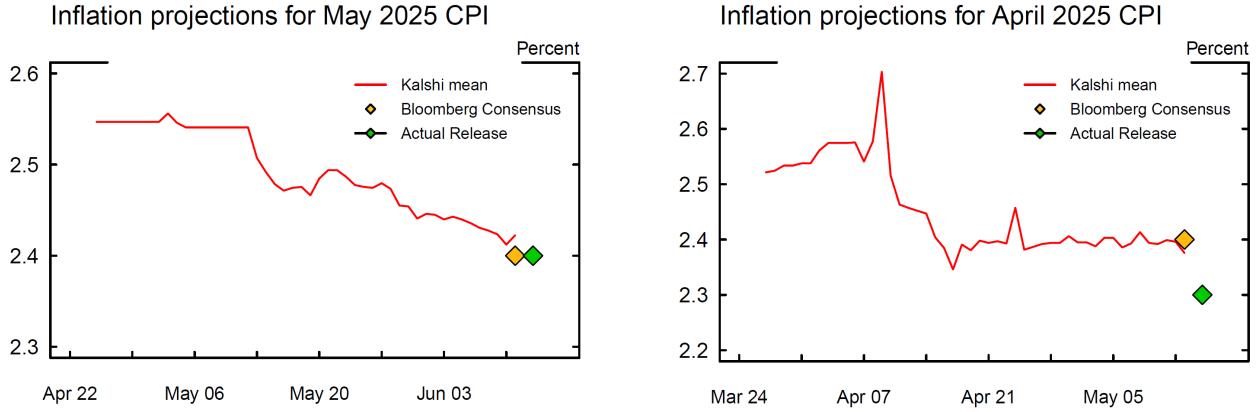


Figure 7: **Kalshi CPI Comparisons to Bloomberg Consensus**

The chart on the left shows the year-over-year May 2025 CPI projection coming from the Kalshi market and the Bloomberg consensus. The chart on the right shows the year-over-year April 2025 CPI projection.

Year-end Projections for CPI and GDP. In addition to year-over-year monthly readings, Kalshi also tracks Q4/Q4 projections for CPI and GDP. The chart on the left of Figure 8 shows that the one-year inflation swap (solid black line) lines up fairly closely with the Kalshi-implied mean (red line). The Blue Chip Economic Indicators 2025 inflation, which is available only at lower frequency, also lines up very closely with the other two approaches.

The chart on the right is the one that is unique to Kalshi. Previously, there did not exist a market-implied forecast of GDP growth. The right panel shows that the Kalshi-implied mean tracked very closely the Survey of Market expectations. We also include the TIPS 2-year real yield as another proxy for growth. All of the series show a decline from the beginning of the year by close to one percentage point, with recent dynamics moving roughly sideways.

Projections for Unemployment. Kalshi offers a rare source of market-based forecasts for labor market indicators such as unemployment and payrolls—variables for which no liquid financial markets currently exist. Aside from prediction markets, forecasts for these releases are primarily derived from surveys. However, survey-based estimates are not updated in real time and are only available at low frequency.

The chart on the left of Figure 9 shows that both the Bloomberg Consensus and the Kalshi-implied mean accurately anticipated the May 2025 unemployment release. For June 2025, both forecasts overestimated the actual unemployment rate, but the Kalshi mean was closer to the realized value than the Bloomberg Consensus.

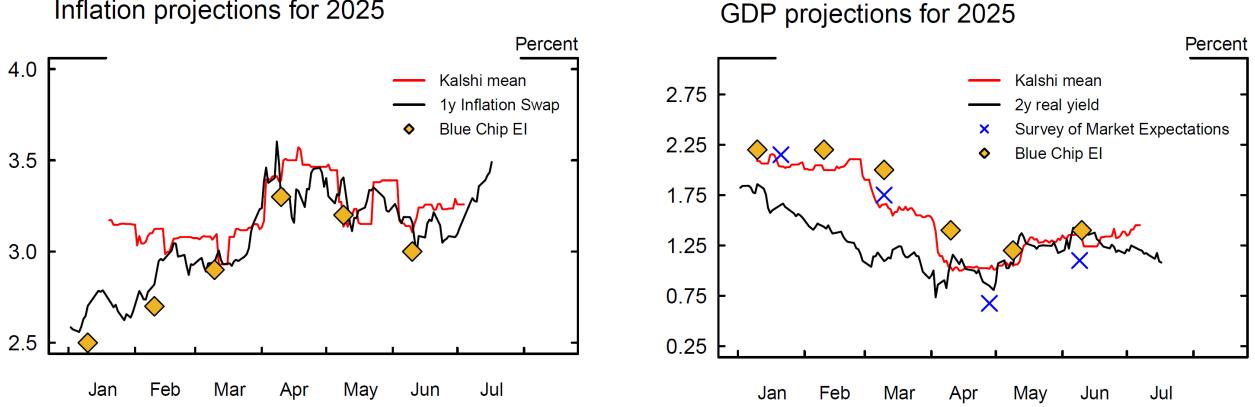


Figure 8: Year of 2025 Comparisons

The chart on the left shows the year of 2025 CPI inflation projection for Kalshi, a one-year inflation swap, and the Blue Chip Economic Indicators consensus expectation for the year 2025. The chart on the right shows the real GDP growth projections for 2025 from Kalshi, the Survey of Market Expectations, and the Blue Chip Economic Indicators. Also included is the TIPS real 2-year yield as a proxy for real growth.

5 Distributional Comparisons to Existing Benchmarks

Kalshi vs Fed Funds Futures. A key strength of the Kalshi market is the probability distribution provided by its market structure. In contrast, fed funds futures require binomial tree assumptions which enforce just two possible outcomes.

For instance, Figure 10 provides a comparison for the September 2025 FOMC meeting. The panel on the left shows the implied probabilities based on two outcomes, no rate change and one 25 basis point cut. In contrast, the Kalshi distribution provides a richer set of outcomes as it does not face the same set of restrictions. While the fed funds futures suggests a weight of 0.75 on a 25 basis point cut, this is likely lumping in weight on lower rate outcomes, as shown by the Kalshi chart on the right. Instead, according to the Kalshi chart, there is much greater uncertainty as investors do not put such a large weight on the modal outcome of a quarter-point rate cut.

We can see a similar issue for the October 2025 FOMC meeting shown in Figure 10. The Kalshi market implies there is nonzero weight on seven different outcomes. When we instead use Fed Funds futures, we have to make an assumption of just two possible outcomes, which clearly implies too little uncertainty.

Kalshi vs SOFR Options. While the fed funds futures can be quite restrictive in formulating probabilities, a suitable alternative is one based on SOFR options. SOFR options have been around since January 2020. One issue with SOFR options is that the contracts that are liquid are for three month periods. This makes them difficult to interpret, as they

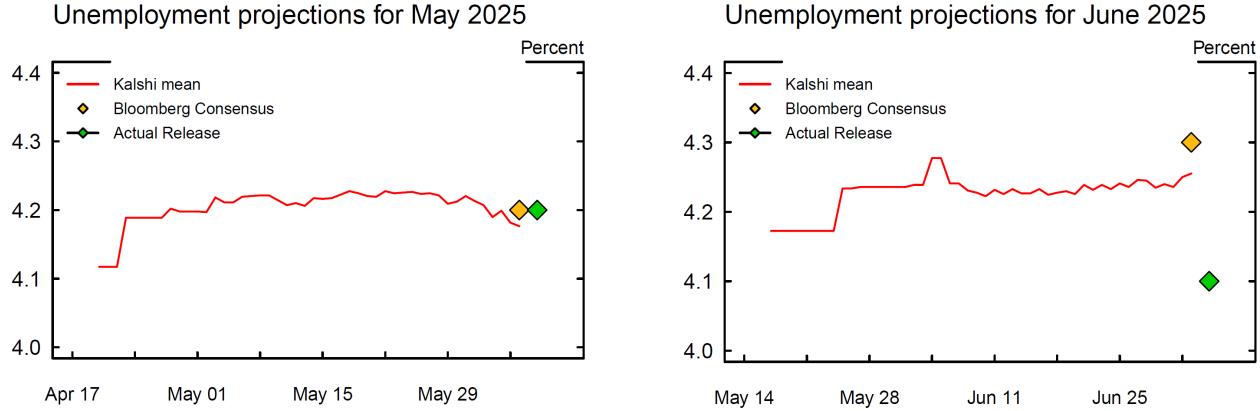


Figure 9: **Unemployment Comparisons**

The chart on the left shows the unemployment projections for May 2025. The chart on the right shows the unemployment projections for June 2025.

average over multiple FOMC meetings. In contrast, the Kalshi distribution is specific to each meeting.

Another issue is that SOFR contracts settle to the repo rate which has a spread with respect to the effective federal funds rate. This spread has grown over time and is expected to continue to grow amid balance sheet runoff by the Federal Reserve. A several basis point difference may seem small, but this can dramatically affect probabilities.

Figure 11 shows the SOFR option-implied distribution for Q4 2025 (the three months to mid-December) implied a modal outcome of no rate cuts. In contrast, the Kalshi distribution, constructed as the average of the September and October densities, along with fed funds futures, implied greater weight on a 25 basis point rate cut. This is likely driven, in part by the roughly 6 basis point spread between SOFR and the effective federal funds rate. While one could consider a crude lateral shift of the SOFR distribution, there's little evidence to suggest the SOFR-EFFR spread follows a normal distribution, so this adjustment could introduce further noise. The fact that the underlying SOFR rate is meaningfully higher implies an upward bias in the probabilities implied by the SOFR distribution. Since the Kalshi market is directly tied to the federal funds rate, it does not suffer from this issue making it the best available density forecast for the funds rate.

Kalshi vs SOFR Investors. Another key distinction between the SOFR market and Kalshi is related to the investors in each market. Kalshi tends to attract the retail investor with its relatively low entry cost. In contrast, the SOFR market tends to have larger institutional investors. It seems plausible that large institutional investors may have greater hedging needs and this could also play a role in the observed upward bias for this period.

The idea is that institutional firms may have large fixed income exposure and may wish

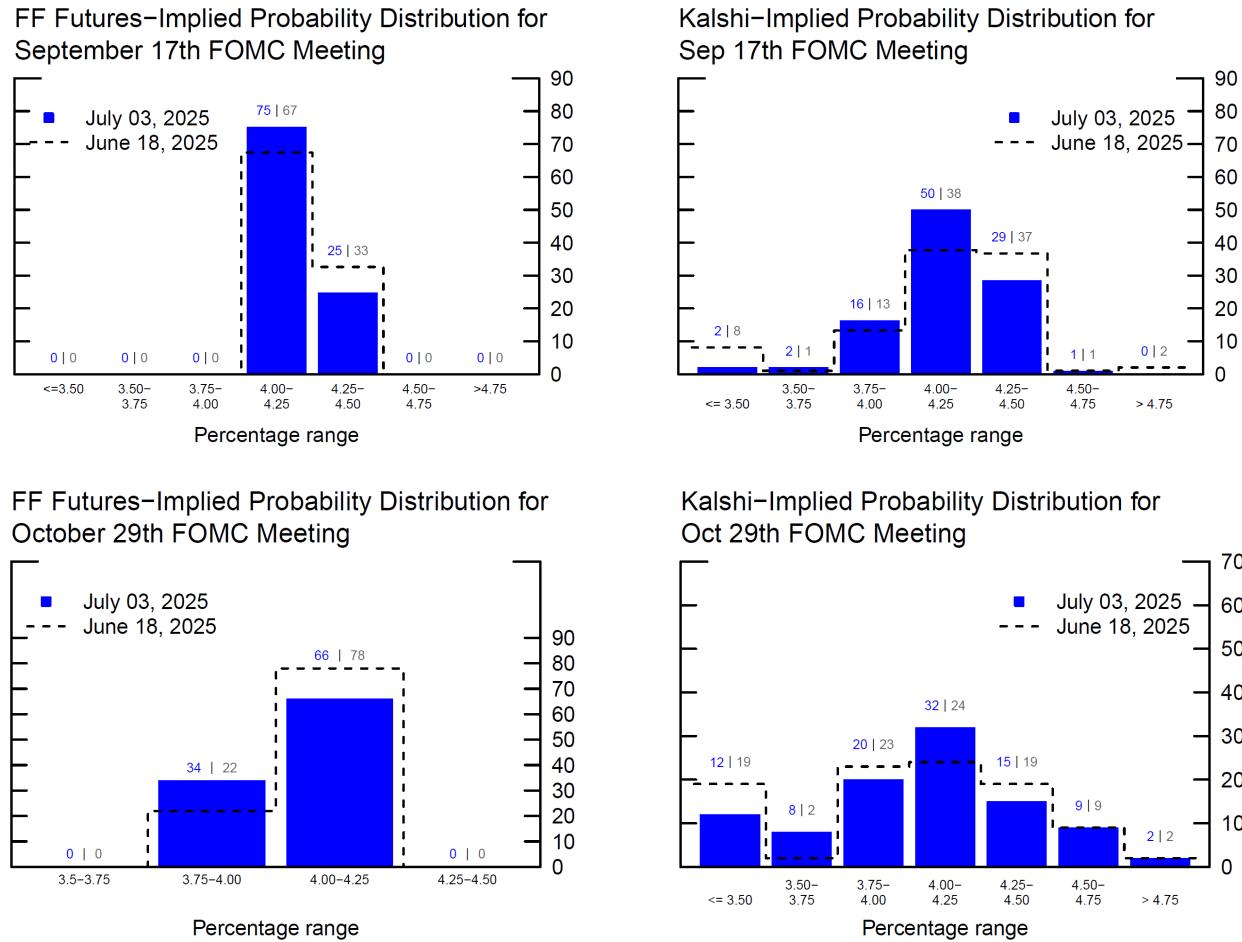


Figure 10: Fed Funds Futures vs Kalshi Sept. and Oct. 2025 FOMC Meetings

The upper left panel shows the implied probability from Fed Funds futures for the September FOMC meeting. We use the price of the Fed Funds futures contract for October to determine the probabilities which are assumed to have just two possible outcomes. The upper right panel shows the corresponding Kalshi distribution that does not enforce the assumption of just two outcomes. The lower left panel shows the implied probability from fed funds futures for the October FOMC meeting. For parsimony, we use the price of the fed funds futures contract for November to determine the probabilities. The lower right panel shows the equivalent Kalshi distribution.

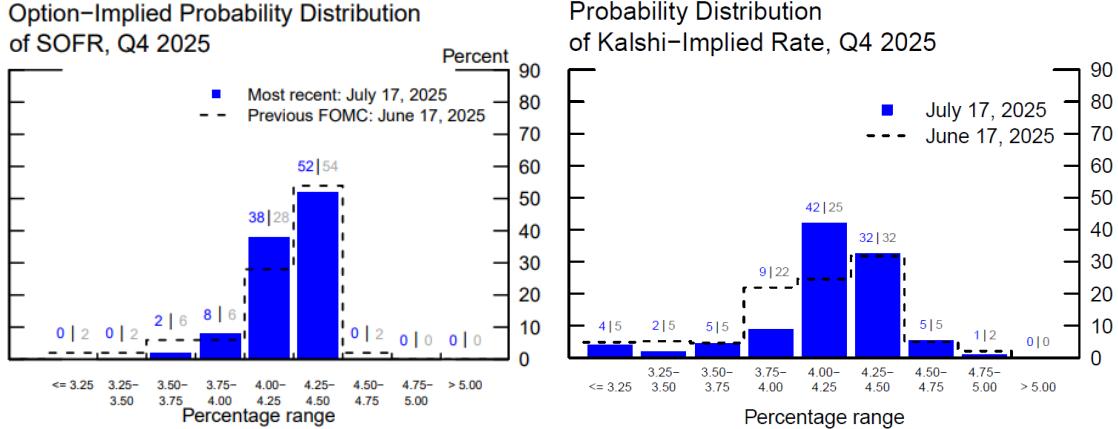


Figure 11: SOFR Options vs Kalshi Q4 2025 FOMC Meeting

The left panel shows the implied probability from SOFR options for the fourth quarter of 2025. This is defined as mid-September to mid-December 2025. The right panel shows the equivalent Kalshi distribution, which is computed by averaging over the September and October 2025 FOMC meetings.

to hedge against a scenario where rates remain elevated or where bond prices may fall. This would push up the demand for options for the no rate change outcome while pushing up the prices of these options, which would increase the implied probability of this outcome. But this would be more indicative of risk premiums rather than expectations. Indeed, survey-based evidence coming from the Survey of Market Expectations (not shown) also suggests greater weight on rate cuts than implied by SOFR options, which is consistent with Kalshi.

2025 Inflation and GDP Growth Distributions. As previously noted, a unique aspect of Kalshi is the availability of real-time GDP growth distributions. Figure 12 shows the Kalshi probability distribution for CPI and real GDP Growth over 2025. Interestingly, it suggests that investors are placing greater weight on outcomes for growth below 1% and for CPI inflation to be above 3.5% when compared to the beginning of the year. These moves seem consistent with market commentary highlighting the potential effects of trade policy developments over this past year.

A read from July 3rd, 2025 on the probability of GDP growth being below 1% was close to 0.4. This might seem large, but the July Blue Chip Economic Indicators consensus forecast for 2025 GDP growth is 1.4, which is roughly consistent with the median of the Kalshi distribution. The consensus forecast for 2025 CPI from the Blue Chip survey is 2.9, which is also close to the median of the Kalshi CPI distribution. However, a key difference between Kalshi and the Blue Chip surveys is the availability of the probability distribution rather than just a single point estimate. The Kalshi distribution shows how uncertain investors are about inflation and GDP growth for this year. While the Survey of

Professional Forecasters also provides distributions for GDP growth and inflation, they are only available at a quarterly frequency. The advantage of high frequency data allows for analyzing shifts in the distribution of GDP outcomes after large news events (such as trade policy changes as shown in Figure 12).

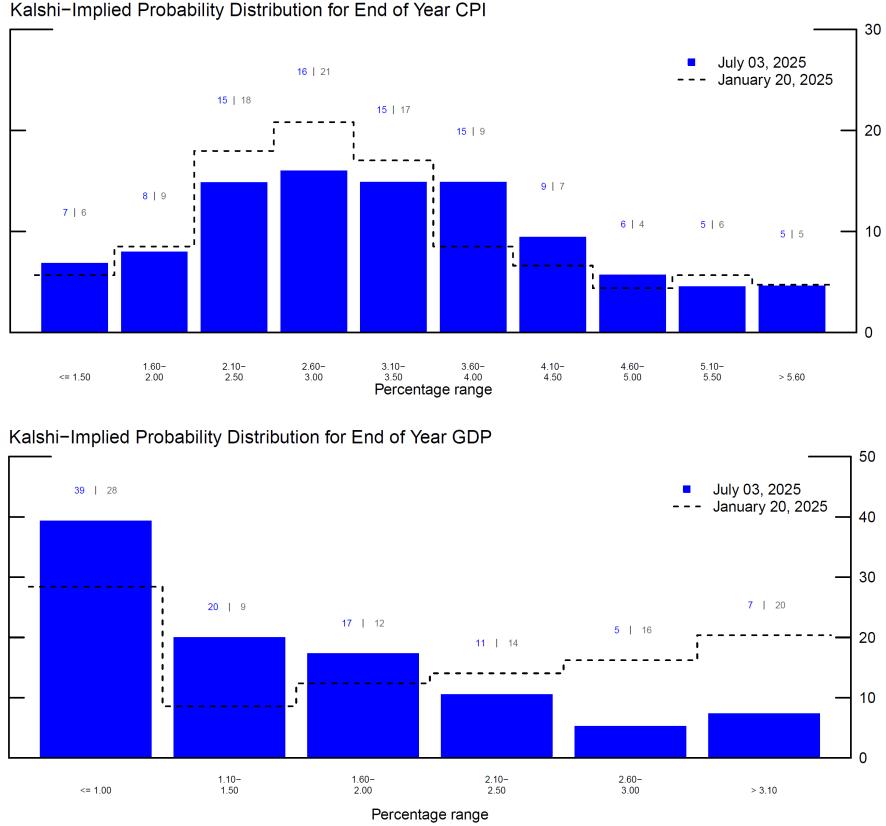


Figure 12: **End of Year 2025 Distributions for CPI and Real GDP Growth**

This chart shows the probability distributions for CPI and real GDP growth for 2025. These are calculated as December 2024 to December 2025 for CPI, and 2024Q4 to 2024Q5 for real GDP growth.

Stagflation risks. Figure 13 shows the evolution of tail risks to CPI and GDP calculated using Kalshi, Survey of Professional Forecasters, and Blue Chip data. Specifically, we plot the daily time series for the weight placed on CPI being greater than 3 percent in the upper left panel and real GDP growth being lower than 1.5 in the upper right panel. We plot the equivalent SPF probabilities based on the first and second quarter readings. We also plot the percent of respondents from Blue Chip Economic Indicators with a modal expectation above 3 percent, though note that this is no way a density forecast. For inflation, we can see that all three series seemed to increase around the beginning of April, consistent with concerns regarding inflation associated with trade developments. We see the probability

come down as news of trade alleviation becomes more prominent later in the sample. We see similar dynamics for real GDP potentially being below 1.5 percent. All of the Kalshi and SPF densities are marginal ones; we have no way of measuring the joint probability of high inflation and low growth.

For the severe stagflation outcomes, with inflation being above 4 percent (lower left panel) or GDP growth being below 0 percent (lower right panel), we see much more weight placed on these outcomes for Kalshi than for the surveys. There are a number of explanations that could explain the difference between Kalshi and the SPF survey, such as the presence of risk premiums or differences in retail investors versus professional forecasters. Nonetheless, the latest probabilities in the Kalshi market seem to be consistent with the second quarter observation coming from SPF (with the exception of the $\geq 4\%$ inflation panel).

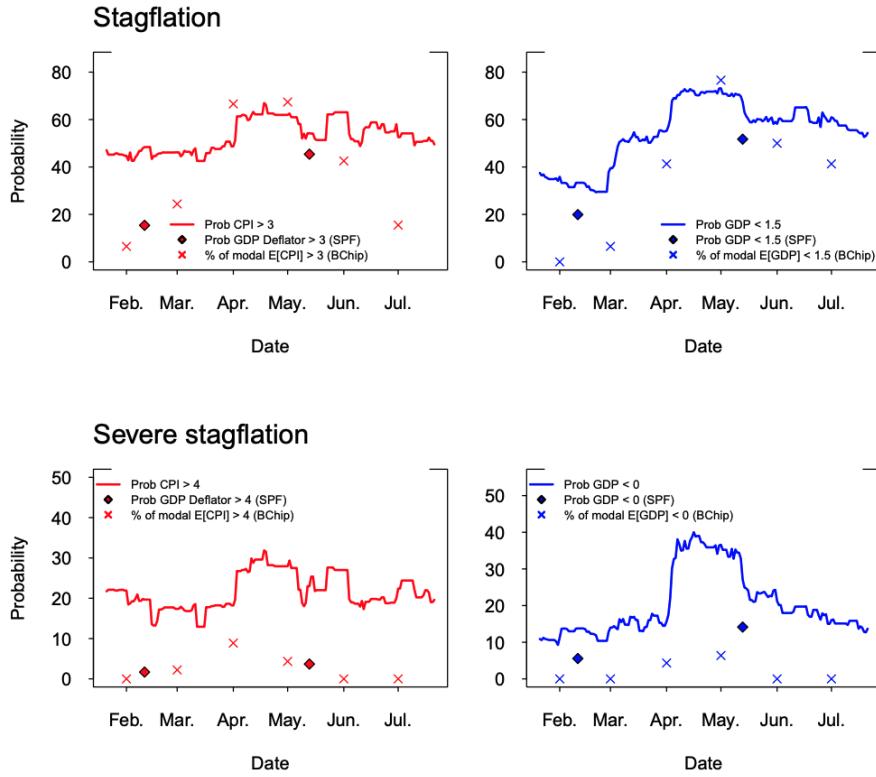


Figure 13: End of Year 2025 Stagflation Risks

This chart shows the probability of tail risks for CPI and real GDP growth for 2025 over time. These are calculated as December 2024 to December 2025 for CPI, and 2024Q4 to 2024Q5 for real GDP growth. Probabilities are created by taking the sum of different bins in each period over time.

6 Forecast Performance of Kalshi

In this section, we explore the forecast performance of Kalshi forecasts of the fed funds rate for each FOMC meeting along with the year-over-year CPI inflation for each month since 2022.

Federal Funds Rate. The Kalshi distribution provides a mean, median, and modal forecast based on its distribution. A natural question relates to how well these elements forecast the federal funds rate after each FOMC meeting.

Earlier, in Figure 1, we showed the mean absolute prediction error, averaging across all FOMC meetings, plotted against the number of days before the FOMC meeting. That figure also shows some comparisons. The forecast performance of Kalshi is roughly consistent with professional forecasters such as those from FRBNY’s Survey of Market Expectations. We plot one-half standard deviations of forecast errors for the survey and one can see overlap with the Kalshi-implied moments. We also plot mean absolute forecast errors coming from fed funds futures (purple line), and note the slight improvement with about 60 days to go for Kalshi. Also of note, the mode coming from Kalshi’s distribution has had a zero absolute average error by the day of the FOMC, which is in contrast to the survey and fed funds futures. The observation that drives this distinction was the September 2024 FOMC, in which there was probability on both a 25 and 50 basis point cut, and Kalshi put greater weight on the 50 basis points that turned out to be correct.

CPI. In Figure 14, we see a similar decline in the average absolute error for CPI annualized inflation forecasts as we get closer to the release date. In contrast to Kalshi, we only observe the Bloomberg Consensus forecast just before the data release and thus cannot evaluate its evolution over time. Thus, the Kalshi can provide a read of expectations for these monthly releases well in advance of the Bloomberg consensus.

For headline CPI, the mean absolute error from Kalshi as of the day of the release is about 7 basis points, while the Bloomberg consensus is about 8 basis points.

Unemployment. Kalshi also provides real-time distributions for expectations of the unemployment rate. As with real GDP growth, options markets do not exist for unemployment, which makes Kalshi unique in terms of providing a distribution for unemployment expectations. Figure 14 shows that the average absolute error for the mean coming from Kalshi is fairly close to the Bloomberg consensus forecast, while the mode tends to jump around as it must take values in increments of 0.1.

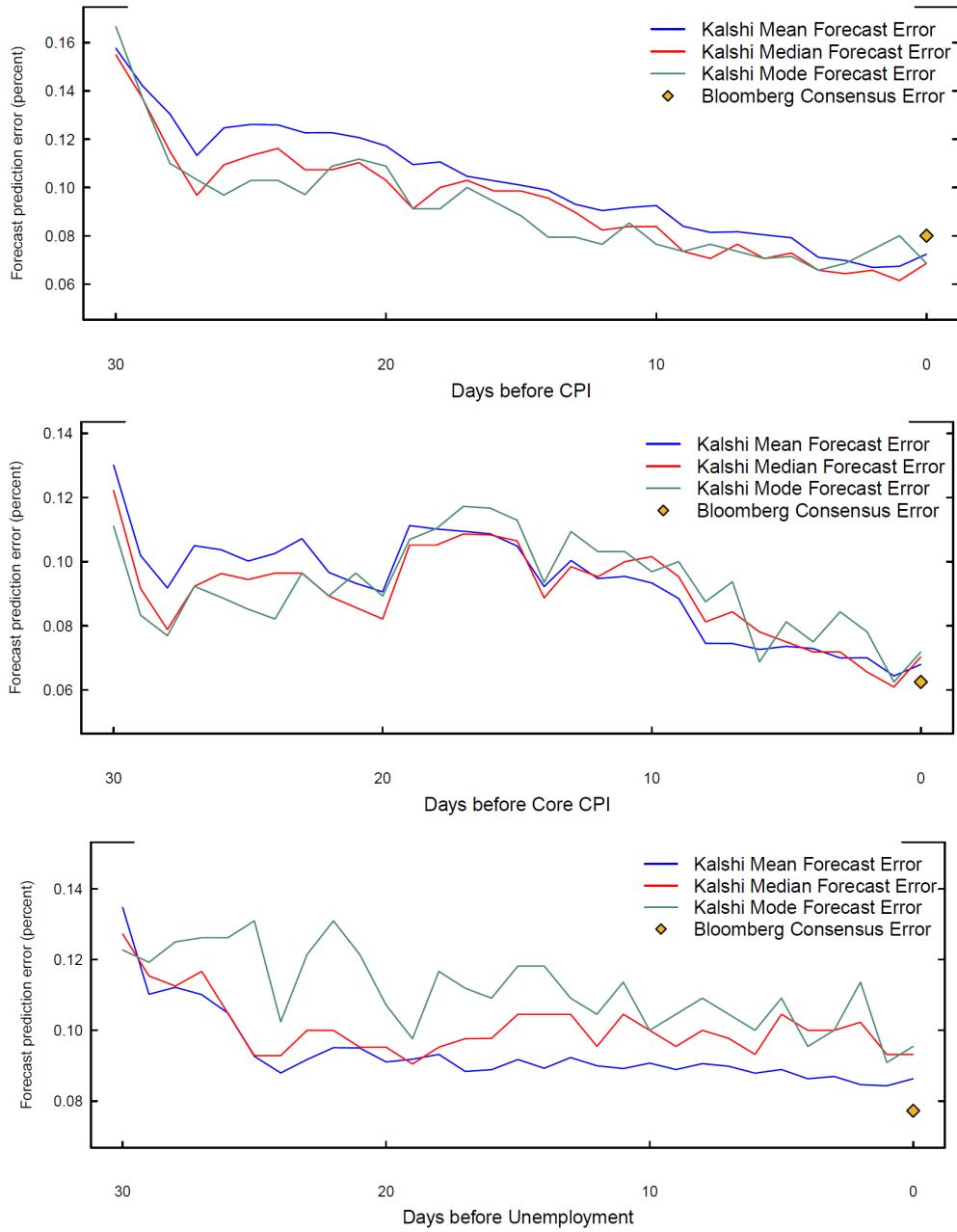


Figure 14: **Headline, Core CPI and Unemployment Forecast Errors Comparison**

This figure compares the mean absolute errors from 50 days out to each headline CPI, core CPI, and unemployment release since 2022.

Significance of differences in forecast accuracy Table 3 compares the mean absolute error and the root mean square error on the day of the release for the Kalshi mean, median and mode forecasts with that from the Bloomberg consensus. Statistical significance from Diebold-Mariano statistics (Diebold and Mariano, 1995) comparing each of the Kalshi forecasts to the Bloomberg consensus is also noted. In some cases, the Kalshi forecast is a significant improvement over the Bloomberg consensus. For example, the Kalshi median and mode have significantly smaller mean absolute error than the Bloomberg consensus for headline CPI. In other cases, there is no statistically significant difference between Kalshi and Bloomberg forecast accuracy. In no case is Kalshi significantly worse than the Bloomberg consensus.

Panel A: Macro Variables				
	Bloomberg	Kalshi Mean	Kalshi Median	Kalshi Mode
Headline CPI				
MAE	0.081	0.069	0.063 *	0.063 *
RMSE	0.100	0.080 **	0.083	0.087
Core CPI				
MAE	0.070	0.070	0.080	0.070
RMSE	0.100	0.090	0.110	0.100
Unemployment Rate				
MAE	0.109	0.117	0.107	0.107
RMSE	0.132	0.136	0.132	0.135

Panel B: Federal Funds Rate				
	FF Futures	Kalshi Mean	Kalshi Median	Kalshi Mode
MAE	0.010	0.010	0.000 **	0.000 **
RMSE	0.020	0.030	0.000 **	0.000 **

Table 3: **Forecast Accuracy: Benchmark Forecasts versus Kalshi**

Panel A reports forecast accuracy relative to the Bloomberg consensus forecast on the day of the release. Panel B reports forecast accuracy relative to fed funds futures on the day of the FOMC. Stars indicate statistically significant differences in forecast accuracy relative to the benchmark based on Diebold–Mariano tests. Stars denote significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

6.1 Probability Integral Transform

As noted earlier, the Kalshi-implied density is under the risk-neutral \mathbf{Q} measure which, given risk premia, is not necessarily the same as the physical \mathbf{P} measure. The extent to

which Kalshi-implied pdfs are distorted by risk premia is an empirical question. If the Kalshi-implied density were indeed the physical density of the future variable, then it is well known that the cumulative distribution function, evaluated at the realized value, should be uniform on the unit interval (see, for example, [Diebold et al. \(1998\)](#)). We assess this in Figure 15 for forecasts for monthly releases of unemployment, CPI (headline and core) and FOMC decisions on the target federal funds rate. These are constructed both 28 days before the release and on the day of the release, but before it. The probability integral transforms generally seem close to uniform. We can test the hypothesis that they are uniform in population using the test statistics:

$$K = \sup_{0 \leq r \leq 1} \Psi(r) \quad (1)$$

and

$$C = \int_0^1 \Psi(r)^2 dr. \quad (2)$$

where $\hat{F}(r)$ is the empirical cdf of the PIT and $\Psi(r) = T^{-1/2}(\hat{F}(r) - r)$, $0 \leq r \leq 1$ ([Darling, 1957](#)). The bootstrap p -values using the bootstrap of ([Rossi and Sekhposyan, 2019](#)) are also shown in Figure 15. In some cases, uniformity is borderline rejected, mostly because low values of inflation and unemployment occur a little too frequently. In other cases, the null of uniformity is not rejected. Overall, while there is some evidence of risk premia overstating the odds of higher inflation and higher unemployment, these probability density functions appear to be fairly well calibrated.

7 Distributional Responses to News

7.1 Fed Funds Rate Responses to Macro News

With access to full distributions, we can uncover new patterns in how macroeconomic news affects higher moments of expectations of the federal funds rate at the next FOMC. Figure 16 shows the average daily response to news for the mean, mode, variance, and skewness coming from the distribution of the federal funds rate for the next FOMC. The news releases we focus on are CPI, PCE inflation, Non-farm payrolls, ISM manufacturing, FOMC statement, and FOMC minutes. We denote all other days as Other.

Fed funds rate mean and mode responses to news. Based on responses since 2022, we see that CPI days tend to have the largest positive effects on the first moment of the federal funds rate distribution. This could be a reflection of the sample period, as there

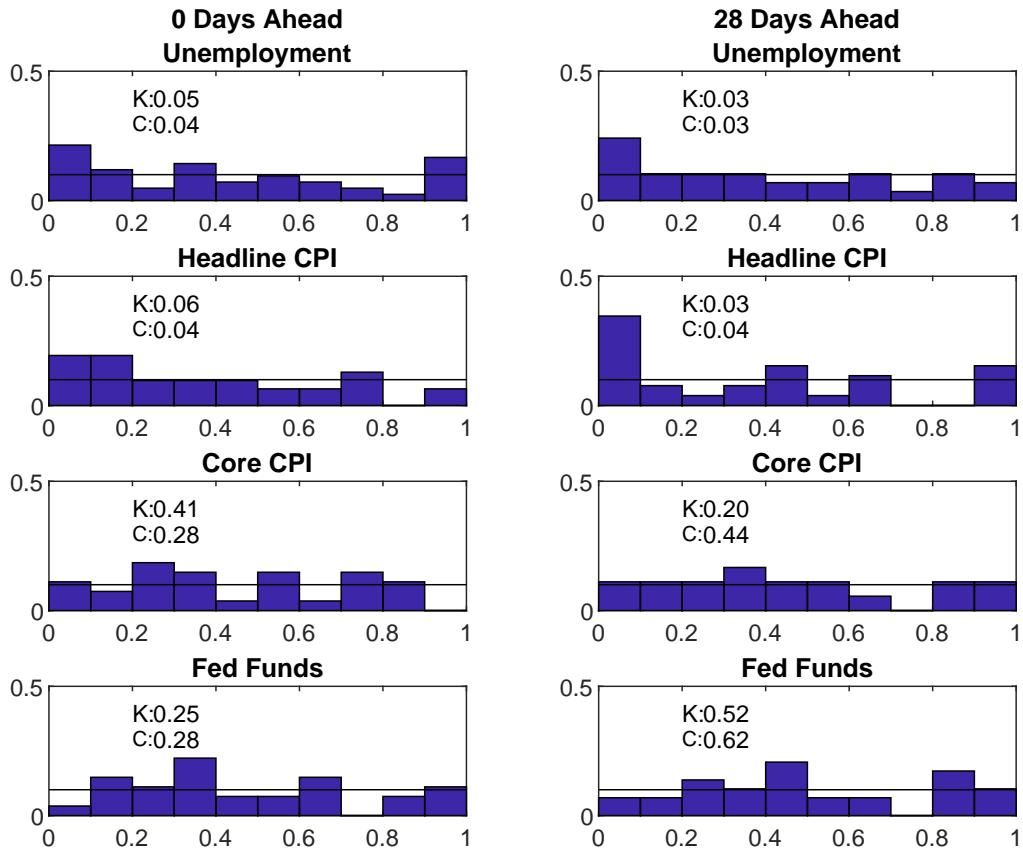


Figure 15: Probability Integral Transform

This figure shows the empirical cumulative distribution function as of 0 and 28 days before unemployment, CPI (headline and core) and FOMC scheduled federal funds rate announcements, all evaluated at the realized value. If the options-implied distribution were equal to the physical distribution, then this probability integral transform would be uniform in population, as shown by the lines. Each panel also reports the p -values from the test statistics k and C , defined in the text, using the bootstrap of [Rossi and Sekhposyan \(2019\)](#)

were several announcements of higher-than-expected inflation in this particular period and is consistent with the importance of inflation for rate setting in the post-pandemic period. We also see that CPI, Non-farm Payrolls, and FOMC Minutes/Statement days on average result in the largest changes in central moments of the distribution of Federal Funds Rates, coinciding with market commentary typically placing the largest emphasis on these events. We are assured that our constructed distributions move significantly more on news release days than other days.

Fed funds rate variance and skewness responses to news. We can also see the effects of news on the variance and skewness of the fed funds rate distributions in panel B of Figure 16. Intuitively, nearly all of the news announcements lower the variance. While variance typically decreases on any day (consistent with a general resolution of uncertainty over time), news days result in larger variance declines than other days, consistent with the idea that news days are informative for understanding future Federal Funds Rate distributions. As one might expect, the largest decline in the variance of the fed funds rate distributions comes on FOMC days, with CPI days generating the second largest decline.

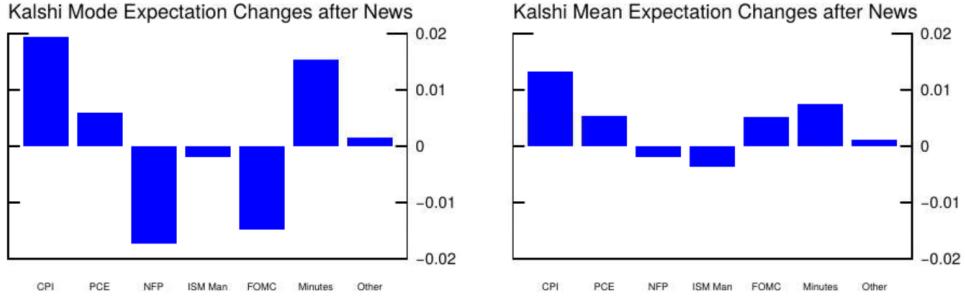
In terms of skewness, we see that nonfarm payrolls days and FOMC days tend to have the largest positive effect. While the mode and mean seem to tend to decline on NFP days, the rise in skewness suggests that Kalshi investors seem to also place relatively more weight on the upper tail of the fed funds rate distributions. In the next sections, instead of just examining the responses associated with particular news days, we will sharpen our focus on the effects of surprises for each news release.

CPI surprise effects on fed funds rate distributions. We also can evaluate how the distribution of the federal funds rate responds to the surprises released in each news announcement. Surprises are computed by taking the difference between the Bloomberg consensus forecast and the realized print. We first consider CPI inflation, split based on how the moments of the Federal Funds rate respond on days of positive and negative surprises, and days of zero surprise (expectations are measured to the nearest tenth of a percentage point). The results are shown in Figure 17.

As expected, the mean of the fed funds rate distribution (left panel) moves positively with inflation shocks. However, the magnitude is asymmetric: the response to positive CPI shocks is four times that of negative shocks. The variance of the distribution declines across all outcomes—reflecting the resolution of uncertainty—but the drop is sharpest when the release meets expectations (zero surprise). Additionally, skewness falls and kurtosis rises independent of the shock’s direction. To establish the statistical significance of these

patterns, we turn to the regression analysis in the next section.

A. Modal and Mean Responses



B. Variance and Skew Responses

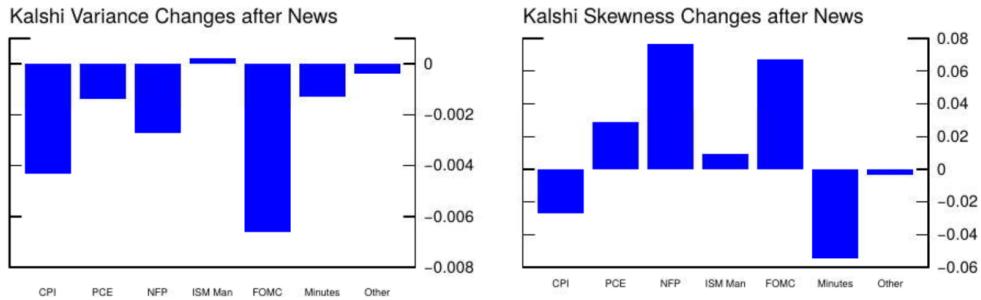


Figure 16: **Federal Funds Rate Distribution Responses to Economic News**

This figure shows the average responses of the distribution of the federal funds rate for the next several FOMC meetings following news releases for CPI, PCE inflation, Non-farm payrolls, ISM Manufacturing, FOMC, and FOMC minutes. Other corresponds to all other days which do not fall into these categories.

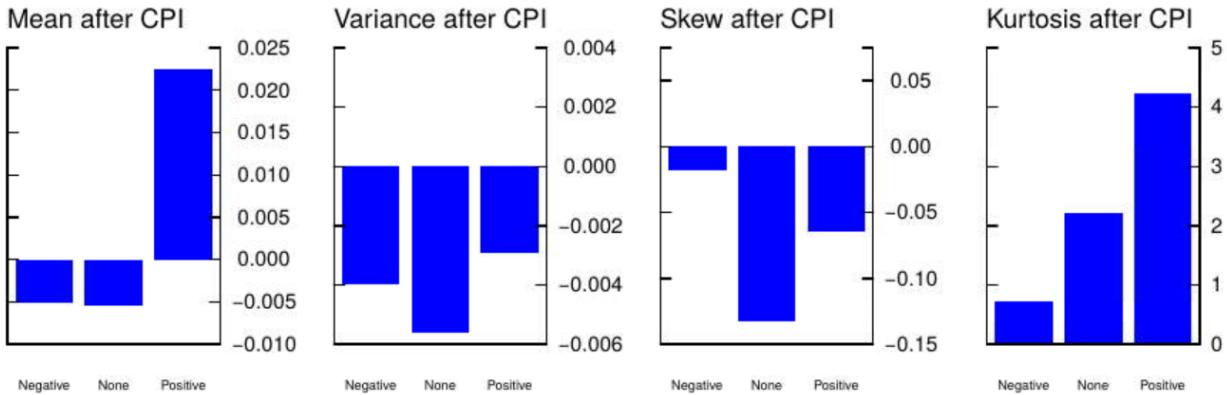


Figure 17: **Federal Funds Rate Distribution Responses to CPI Inflation Surprises**

This figure shows the average responses of the distribution of the federal funds rate for the next several FOMC meetings following positive, negative and zero news from the CPI inflation release.

7.2 Event-study regressions for fed funds rate beliefs

7.2.1 Macro news surprises

We next turn to a more systematic analysis of the effects of surprises on the probability density of the federal funds rate. We consider event-study regressions of the form:

$$\Delta y_t = \beta_0 + \beta_1 S_t + \varepsilon_t \quad (3)$$

where Δy_t denotes the one day change in a moment of the federal funds distribution for the next FOMC meeting on day t and S_t denotes the surprise component of an announcement coming out on that day. The regression is run over all days of a particular announcement type. The announcement types considered are CPI, PCE and nonfarm payrolls. The constant measures the effect of the announcement in the absence of any surprise.

CPI significant effect on fed funds rate. The results are shown in Panel A of Table 4. The mean, median and mode of the funds rate all respond significantly to a CPI surprise with a 10 basis point surprise resulting in a 3 to 4 basis point rise in the central moments of the federal funds rate. We also see that independent of the surprise, the variance tends to fall, as the constant is negative and significant.

PCE less significant effect. Likewise, PCE surprises also have significant effects, but to a much lesser extent, as shown in Panel B of Table 4. This is consistent with market participants and investors paying more attention to CPI, which is more timely. Moreover, much of PCE inflation can be computed based on existing releases of CPI which could explain the smaller effects.

Nonfarm payrolls, no significance. In Panel C of Table 4, nonfarm payrolls show a positive relationship with the first moments of the fed funds rate distribution, but there is no statistical significance beyond the constant for the mean. This seems consistent with investors placing much greater emphasis on monetary policy's potential response to inflation over the 2022-2025 period when compared to jobs, with the unemployment rate being historically low.

7.2.2 Monetary policy surprises

Table 5 presents the response of the federal funds rate distribution to the monetary policy shocks of [Acosta et al. \(2025\)](#). This separately identifies shocks in two communication

Panel A. CPI Headline YoY

	Kalshi Fed Funds Rate Distribution					
	Mean	Median	Mode	Variance	Skewness	Kurtosis
CPI Surprise	0.320*** (0.052)	0.388*** (0.079)	0.413*** (0.079)	-0.002 (0.011)	-0.183 (0.448)	3.666 (4.676)
Constant	0.007 (0.005)	0.012 (0.008)	0.017* (0.009)	-0.004*** (0.001)	-0.028 (0.048)	1.853*** (0.540)
Observations	113	113	113	113	113	113
R^2	0.379	0.255	0.256	0.001	0.002	0.006

Panel B. PCE Headline YoY

	Kalshi Fed Funds Rate Distribution					
	Mean	Median	Mode	Variance	Skewness	Kurtosis
PCE Surprise	0.012** (0.004)	0.015* (0.008)	0.012* (0.007)	-0.001 (0.001)	0.001 (0.040)	-0.438* (0.257)
Constant	-0.003 (0.006)	-0.014* (0.008)	-0.017* (0.009)	-0.002* (0.001)	0.068 (0.043)	1.827*** (0.573)
Observations	113	113	113	113	113	113
R^2	0.060	0.040	0.023	0.007	0.000	0.007

Panel C. Nonfarm Payrolls

	Kalshi Fed Funds Rate Distribution					
	Mean	Median	Mode	Variance	Skewness	Kurtosis
NFP Surprise	0.053 (0.032)	0.045 (0.051)	0.045 (0.051)	0.010 (0.009)	-0.061 (0.455)	-4.946 (3.440)
Constant	0.005** (0.002)	0.004 (0.005)	0.004 (0.005)	-0.001 (0.001)	0.037 (0.030)	-0.156 (0.550)
Observations	108	108	108	108	108	108
R^2	0.056	0.008	0.008	0.011	0.000	0.007

Table 4: Kalshi Fed Funds Rate Distribution Responses to Macro Surprises

Notes: This table reports estimates of equation (3) using robust standard errors (HC3). Columns represent the change in moments of the Federal Funds Rate distribution on the day of the news release (end of previous day to end of day of release). Surprises are measured as the actual released value minus the Bloomberg survey expectation. Units are percentage points for CPI and PCE (year-over-year) and 100,000s of payrolls for Nonfarm Payrolls. Stars denote significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

windows: the statement window and the press conference window. We study the effects of both monetary policy shocks on the Kalshi-implied federal funds rate distribution at horizons out to about 6 months jointly. The results highlight a clear distinction between the two communication windows. During the statement window, the shock primarily shifts the level of rates: the mean, median, and mode all respond positively and significantly. This is not surprising as of course the statement includes the announcement about the current target for the federal funds rate. We also observe a significant rise in variance, indicating that the tighter policy generates some immediate dispersion in market views.

Press conference effect on skewness. Conversely, we find that the press conference shock has a positive, albeit statistically insignificant, effect on the central tendency (mean, median, or mode). This lack of significance may stem from the short maturity of the Kalshi Fed funds contracts, which limits the sample to a six-month horizon and the press conference obviously does not make announcements about the current funds rate target. However, the press conference significantly alters the shape of the distribution, causing a sharp decline in skewness. This negative shift could possibly reflect that more restrictive than expected communication during the press conference effectively truncates the “right tail” of the distribution. Tighter monetary policy in the press conference could be resolving upside uncertainty—capping the risk of higher rates—while leaving downside risks intact.

Kalshi Fed Funds Rate Distribution						
	Mean	Median	Mode	Variance	Skewness	Kurtosis
MP Statement Shock	0.872*** (0.236)	1.098** (0.427)	1.233* (0.681)	0.249* (0.144)	-0.763 (2.344)	-6.609 (7.603)
MP Press Conference Shock	0.011 (0.319)	0.502 (0.318)	0.339 (0.905)	-0.032 (0.159)	-2.875** (1.285)	-7.807 (7.299)
Constant	0.003 (0.004)	-0.004 (0.010)	-0.002 (0.013)	-0.007** (0.003)	0.050 (0.053)	0.384 (0.320)
Observations	94	94	94	94	94	94
R^2	0.165	0.106	0.041	0.054	0.050	0.013

Table 5: **Kalshi Fed Funds Rate Distribution Responses to MP Shocks**

Notes: Robust standard errors (HC3) in parentheses. Columns report changes in moments of the federal funds rate distribution on the day of the news release for meetings more than one month ahead (end of previous day to end of release day). Monetary policy shocks are measured using the San Francisco Fed USMPD database. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

8 Conclusions

This paper has introduced Kalshi macroeconomic prediction markets as a novel, high-frequency, and distributionally rich source of expectations data. Using newly available contracts across a broad set of macroeconomic indicators, we have shown that Kalshi-implied distributions are well-behaved, responsive to news, and comparable in forecasting accuracy to established benchmarks such as the Survey of Market Expectations and the Bloomberg consensus. In several cases, they provide unique insights—particularly for variables like GDP growth, core inflation, unemployment, and payrolls, for which no other market-based distributions currently exist. We have also argued that they provide the only credible measures of distributional beliefs about decisions at specific FOMC meetings.

Our results highlight several key advantages. First, Kalshi’s forecasts for the federal funds rate and CPI provide statistically significant improvements over fed funds futures and professional forecasters, all while providing continuously updated full distributions rather than infrequent point estimates. The mode of the Kalshi distribution, for example, has perfectly matched the realized federal funds rate by the day of each meeting since 2022, a feat not achieved by either surveys or futures. Second, these markets capture rich distributional dynamics—such as tail risks and asymmetries in higher moments—that are unavailable from traditional sources. For instance, we find that monetary policy press conference shocks tend to significantly reduce skewness in the Federal Funds rate distribution. Third, the accessibility of Kalshi to retail traders introduces a perspective distinct from institutionally dominated markets, potentially offering a complementary lens on expectations formation.

Together, these findings suggest that prediction markets can serve as a valuable complement to existing forecast tools in both research and policy settings. By providing transparent, continuously updated, and economically interpretable measures of expectations with competitive forecast performance, they open new avenues for studying monetary policy transmission, market sentiment, and macroeconomic uncertainty. As these markets mature and liquidity deepens, their potential to enhance real-time policy analysis and academic research will only grow over time.

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Appendix

A Midpoint of Bid-Ask Spreads

Another approach to constructing the PDFs for the federal funds rate expectations is to take the midpoint of the bid-ask spread, as opposed to using the prices based on the last trade. Our forecast error results are shown in Figure A.1 based on this approach. One can see that the forecast errors spike quite a bit more, indicating some reliability issues, most likely due to issues surrounding the tails of the distribution. Because of these issues, we maintain focus on the last trade for our main results.

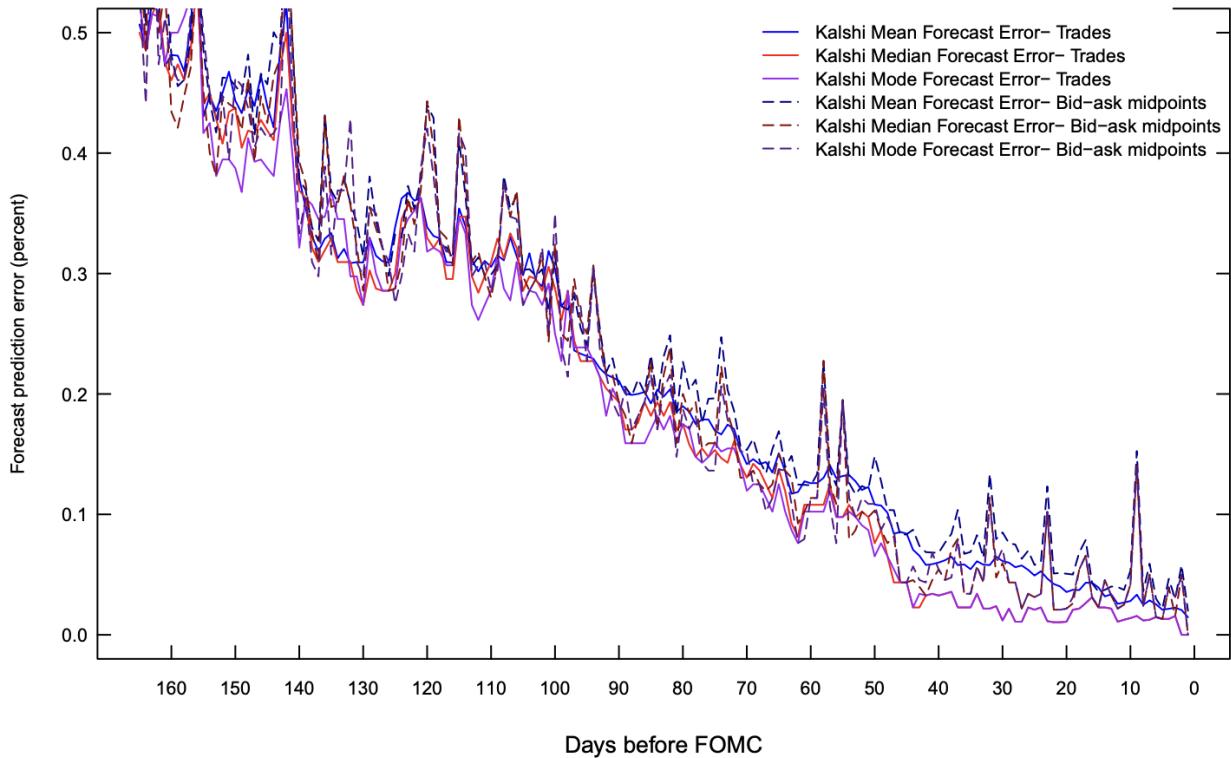


Figure A.1: Midpoint of Bid-Ask Spread: Fed Funds Rate Forecast Errors

This figure compares the mean absolute errors from 160 days out to each FOMC for the effective federal funds rate since 2022. Both the last trade and bid-ask midpoints are plotted.