SimFOMC

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US Rates Strategy Joseph Abate September 1, 2026 joseph.abate@smbcnikko-si.com 1 212 893-1592 Sim FOMC AI and large language models are already used to analyze and characterize Fed speeches. They can accurately sort commentary by hawkishness and mimic human reasoning. But AI FOMC simulations are less accurate than mechanical models. Modeling FOMC deliberations turns out to be harder than classifying their commentary. • Analysts regularly examine Fed commentary and based on their experience and context, determine whether it is hawkish or dovish . But this approach is not scientific. • ChatGPT can break down and rank the relative hawkishness of Fed commentary. It accurately mimics human reasoning and is closer to human logic than simple dictionary-based assessments . • AI can create simulated FOMC meetings. These involve simulating FOMC members interacting with each other in a “lab” structured like an actual FOMC meeting. • Creating a simWarsh is complicated because he provides little information about his reaction function and his commentary is terse. The Fed Chair has two roles – as a voter and as the “agenda setter”. • AI simulations suggest that political pressure is more likely to change meeting outcomes when the criticism is public . Simulated outcomes are unaffected when the pressure is privately applied to the Chair; if the view is too out of consensus, other FOMC members will ignore it. Dissecting Fedspeak Economists and analysts regularly examine Fed commentary and based on their experience and context, determine whether it is hawkish or dovish . But this approach is not scientific. Judgements are not consistently repeatable nor are the interpretations universal. 1 In addition, these judgments cannot be quantified so it is impossible to express how much an FOMC member’s views may have changed. As technology has improved, economists increasingly use classification models that “read” and score Fedspeak automatically. The simplest versions are based on dictionaries of sensitive words that are associated with particular policy preferences . These are ranked by word frequencies and associations. Hawkish dictionary entries might include “inflation” or descriptions like “robust” and “overheating”. Dictionary models can count the ratio of hawkish to dovish words to construct a relative 1 Context matters; the same wording may sound more hawkish to economists following the release of a much stronger than expected payroll reading a few weeks earlier.

SMBC US Rates Strategy 2 “hawkish score” . 2 Because the model and scoring can be used repeatedly and across FOMC members and speeches, it can measure the relative hawkishness of Fed commentary over time. But these scores are only as effective as the depth and comprehensiveness of their dictionaries . They miss the context of how the word is used. “Inflation has moderated”, “moderate wage inflation”, and “members were less concerned about oil price inflation” have different interpretations . Instead, more complicated, large language models consider the probability a word like “inflation” might be used with “moderate”, “wage”, or “concern”. Hansen and Kazinnik compare ChatGPT and dictionary- based models to economists’ judgments of the relative hawkishness of 500 random ly selected sentences used in FOMC announcements between 2010-2020. 3 Sentences were graded on a scale of -1 (dovish) to 1 (hawkish). Neutral statements were graded 0. ChatGPT produced gradings that were closer to economists’ assessments than dictionary -based models. Indeed, ChatGPT appears to accurately mimic human reasoning . As it takes only a few seconds to run a Fed speech through ChatGPT, economists might be able to spend more of their time engaged in more productive work – like forecasting Fed policy. Meet the Sims If AI can accurately reflect human reasoning from Fed officials’ commentary, it should theoretically be possible to create FOMC meeting simulations using current data to generate policy predictions. 4 Structurally, these require simulating FOMC agents who meet, debate and deliberate over the current data just like their human counterparts but in a computer "lab" modeled like the actual meeting. Kazinnik and Sinclair test out such a structure. They first create simulated versions of the FOMC members based on their biographies, known policy statements, and any recent speeches. These agents are fed recent macro and financial market data along with their previous FOMC voting patterns. Each regional bank president is given simulated Beige Book synopses. Creating the "sims" is difficult, if there is little background information on the member's views as in the case of new joiner. And, in the case of simWarsh, this is further complicated by the new Chair's policy of providing little information about his reaction function and the terseness of his statements and press conferences. FOMC meeting structure The background data and personas are then interacted with each other in a computer lab that mimics the actual structure of an FOMC meeting. In an actual FOMC meetin g, the Board's staff economists present the Committee with forecasts and alternative scenarios. FOMC members then follow with prepared remarks expressing their forecasts and what they believe is the appropriate policy path. The Chair then proposes a policy path that reflects these views and is informed by the Board staff projections. FOMC members deliberate and then vote. The meeting structure means the Chair plays two roles – first as a deliberating voter like the other FOMC 2 See, "Constructing a Dictionary for Financial Stability", R. Correa, K. Garud, J-M. Londono-Yarce, and N. Mislang, Board of Governors, June 2017. 3 See, "Can ChatGPT Decipher Fedspeak?", A. Lundgaard Hansen, and S. Kazinnik, Federal Reserve Bank of Richmond, April 10, 2024. 4 See, "FOMC in silico: A Multiagent System for Monetary Policy Decision Modeling", S. Kazinnik and T. Sinclair, Stanford University and George Washington University, July 12, 2026

SMBC US Rates Strategy 3 members, and second, as the "agenda setter" who summarizes the other members policy views that are later submitted for voting. Dissents are less attempts to overrule the Chair and the consensus, and more efforts to express alternative views. They have become rarer over time; over the 7094 votes on interest rate policy between 1957 and 2013, only 6% were dissents. 5 Since 2013, the dissent share has fallen to 3.7% even with this year's pickup (Figure 1). 6 Dissents are more common from regional bank presidents than Fed governors (Figure 2). Of the 49 vote dissents since 2013, only 12 have come from Fed governors. Of these, 4 have occurred this year, and a single governor accounts for half of the total since 2013 (Miran). The low volume of dissents may reflect a shift in the leadership style of the Chair – recent chairs have been more consensus oriented than before 2000. Fed Chair Warsh has argued that consensus building may have led to some "groupthink" at FOMC meetings. Meetings need to be more like "family fights" – more confrontational policy debates. SimDeliberation and results How accurate are AI-based FOMC simulations? Kazinnik and Sinclair simulate the outcomes of 218 meetings between 2000-26, of which 74 involved a change in the funds target. The mean absolute forecast error for each meeting was 8bp which is slightly higher than other models using Monte Carlo simulations. AI models are sensitive to false memory effects. 7 Data used to train the model may not be timestamped so events that occur after the training cutoff can still influence AI predictions; predictions may be 5 See, "Making Sense of Dissents: A History of FOMC Dissents", D. Thornton and D. Wheelock, Federal Reserve Bank of St. Louis Review, Q3 2014 6 We focus on rate-related dissents rather than those about policy language or implementation (balance sheet). The dissent rate since 2013 is still low (5%) if we include these additional dissents. 7 See, "Evaluating Inflation Forecasts of Generative AI", M. J. Alam, S. Boyle, and T. Sekhposyan, Federal Reserve Bank of San Francisco, January 2026. Figure 1: Dissent share (% votes) Figure 2 : Dissent distribution (% dissents) Source: Federal Reserve, SMBC Nikko Source: Federal Reserve, SMBC Nikko 0 1 2 3 4 5 6 7 1957-2013 1994-2013 2013-2026 0 20 40 60 80 100 1957-2013 1994-2013 2013-2026 President Governors

SMBC US Rates Strategy 4 unintentional " memories " of future events. This helps explain why AI forecasts of inflation perform better within the sample period than outside it. However, false memories may not be the reason for the FOMC prediction errors; the errors are about the same before and after the training cutoff with data that the simulation would not have seen. Whatever the cause, the FOMC simulation results suggest that while AI can reasonably mimic humans for deciphering Fedspeak it has a much harder time capturing the essence of FOMC interactions and deliberations . Political pressure AI based simulations allow modelers to test out different hypotheses about FOMC meetings. Given the difficulty of capturing FOMC deliberations accurately in simula tions this "lab work" is probably somewhat speculative. That said, Kazinnik and Sinclair test whether political pressure influences meeting outcomes . They explore two channels. In the first, the Fed chair reflects the Administration's views but the rest of the FOMC is unaware. This pressure shows up with the Chair's agenda setting – instead of summarizing the members' prepared marks and submitting the result for deliberation, the Chair submits a biased policy statement for deliberation. The AI sim results suggest that if the Chair's proposal is too far outside the consensus, the other FOMC members will ignore it . Interestingly, the last time that a Fed Chair dissented was in 1939; and in the history of the Fed there have only been 3 such dissents. In the second, all FOMC members are publicly pressured to cut rates by the administration. The simulation results suggest that this has more of an effect on policy decisions. Kazinnik and Sinclair find that public pressure moves Committee voting 10% closer to the administration's view. Interestingly, this seems to be because the public pressure makes the FOMC more coordinated by changing individual FOMC members' views.

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