

U.S. Federal Reserve Monetary Policy: Systematic or Discretionary Based on Real-Time Evidence

Zachary Wong

Walter Payton College Prep, 1034 N Wells St, Chicago, Illinois, 60610, USA; zachary.e.wong@gmail.com

ABSTRACT: In this paper, we evaluate the extent to which the U.S. Federal Reserve interest rate policy actions represent systematic responses to macroeconomic conditions versus discretionary or inertial responses when analysis is limited to real-time information. We utilize vintage-aligned datasets to constrain models to information available to the Federal Open Market Committee at the time of each decision. Rather than treat policy action as one continuous decision function, we decomposed each decision into two distinct components: direction, representing a hike or cut; and magnitude, representing the extent to which the Federal Reserve is moving in that direction. From that split, we use a variety of methods (machine learning, Taylor Rule, etc.) to model each sub-decision, applying expanding-window backtesting to maintain real-time fidelity. We found that while the direction component is highly systematic, with simple rules performing accurate predictions on par or better than machine learning, the magnitude was less rule-like, implying flexibility. Based on counterfactual simulations from a stylized New Keynesian model, these flexibilities result in small deviations during stable periods, but are meaningful during periods of stress. We conclude that monetary policy is largely rule-based in direction, but discretion plays a more important role in magnitude, especially during crisis periods.

KEYWORDS: Economics, Macroeconomics, Monetary Policy, Real-time Data, Machine Learning.

■ Introduction

The Federal Reserve's policy decisions have a significant impact on metrics such as inflation, employment, and financial stability. To that extent, it has been researched thoroughly, with some claiming that financial policy is often a discretionary judgment under uncertainty and based on a wide host of factors, while others point to it following more systematic patterns or rules (e.g., Taylor rule, a simple formula relating interest rates and factors such as output gap and inflation).¹

However, most studies on systematic monetary policy use revised ex post data that policymakers of the past could not have known with such accuracy. Data revisions often occur months or years after they were relevant to policymakers, directly leading to hindsight bias.^{3,4} This led us to hypothesize that apparent policy "mistakes" may disappear under real-time data constraints. Using real-time data allows for clean inference about decision structure, and predictability under such constraints is evidence of systematic behavior.

Machine learning has been shown to have success in macro forecasting and high-dimensional relationships, which are potentially useful in predicting complex economic relationships and policy analysis for decisions like the Federal Reserve's interest rates.^{5,6} However, as monetary policy is low-frequency in our sample, often without changes for years, the data available for model training is extremely limited. Additionally, as we later show, factors like institutional inertia play a large role in the decisions they make, making machine learning forecast accuracy alone insufficient for policy interpretation.

Rather than investigate whether algorithmic policy can "beat" the Federal Reserve in decision-making, we ask what

predictability or lack thereof says about the observed policy structure of the US Reserve system. While economic research often treats policy as a single continuous determination, that choice may overly simplify distinct sources of systematic behavior and discretion. Thus, we break each decision down into direction and magnitude components and evaluate each independently. While we acknowledge the small sample size inherent to institutional monetary policies such as the FOMC decision structure and the resulting limitations of the study, they are not faults of methodology but unavoidable in the analysis of central bank decision-making. We use these changes to compare machine learning models to structural benchmarks, as well as review the consistency of policy decisions based on economic regimes and build illustrative counterfactual simulations using stylized New Keynesian models. Our models and methodology were designed to allow us to distinguish true discretionary behaviors from noise generated by factors such as data revisions and institutional inertia. Based on these analyses, we assess the macroeconomic implications of systematic versus discretionary policy paths.

In this manner, we focus on three main contributions: First, we eliminate the hindsight bias common in policy analysis by using strict real-time information. Second, we break down interest rate decisions into direction and magnitude, allowing us to highlight behavioral differences between the two. Lastly, we show that discretionary deviations from systematic rules are often limited but become meaningful during crises.

■ Data and Real-Time Information Structure

Real-Time Macroeconomic Data:

The primary macroeconomic predictors we used to predict the Federal Reserve's interest rates were taken from the Federal Reserve Bank of Philadelphia's Real-Time Data Set for Macroeconomists (RTDSM).^{4,16} These predictors include inflation, core inflation, consumption growth, labor market utilization, and output indicators. This dataset was necessary to maintain the scope of information the models received, limited to the latest data release available before each FOMC decision. Additionally, we accounted for consumer sentiment and expectations using the University of Michigan inflation expectations and consumer sentiment index.²⁰ All of this data was forward-filled to decision dates, and through these methods, we prevent models from using revised ex post information, which is essential to prevent models from exploiting information unavailable to policymakers of the time.³

Policy Decisions:

The specific metric of policy we attempt to predict is the midpoint of the Federal funds rate target ranges, obtained from FRED and FOMC documentation.^{17,19} We record every identified date that the Federal Reserve changes this midpoint, labeling that a decision. In this manner, we constructed two datasets. The primary set we analyze is a decision-event dataset that only includes meetings with these rate changes, focusing only on active decisions. The secondary dataset is a meeting-level dataset that includes all of the holds in the dataset and thus enables 3-class classification (hike, hold, cut). Because we limit the decision-event dataset to only hikes and cuts, we can avoid inflated accuracy from predicting "no change," as that is the vast majority of the dataset. For that reason, this paper is based on the primary dataset entirely, with the secondary only existing for robustness.

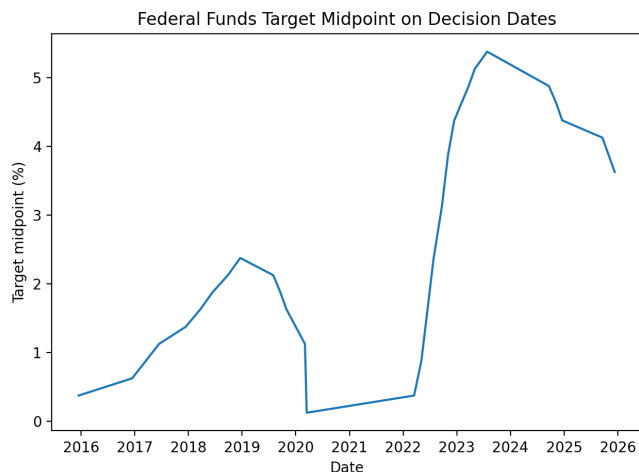


Figure 1: A visualization of the changes in the Federal Funds Rate over time.

Figure 1 illustrates that changes in the Federal Funds Rate tend to happen in clear cycles, not isolated and random movements. Periods of repeated increases or decreases suggest that the policy decisions move consistently in the same direction during a tightening or easing cycle, pointing to the idea of policy inertia.

■ Methods

Decomposition of Policy Decisions:

Policy decisions are decomposed into two distinct components: direction, a measure of whether the policy decision is a rate hike or cut, and magnitude, measuring the extent of rate change in percentage points. This reflects one of our core assumptions that the decision to move rates and the choice of how much to move them may be governed by different core logics and levels of discretion. This aligns with the documented behavior of policymakers sequentially discussing whether to adjust policy before deciding how much, supported by historical accounts of FOMC deliberations.¹⁵

Models:

We utilize two machine learning models to predict the direction of policy: a logistic regression model and a random forest classifier. We also utilize two machine learning models to predict the magnitude of policy: a ridge regression model and a random forest regression model. We utilize a Taylor-type rule to model economic decisions and interest rates based on a rigid, systematic formula.^{1,2} Expanding-window backtests were used to train and test models in the face of our limited dataset, as it mimics real-time learning while avoiding look-ahead bias.

Baselines:

We use two simple baseline comparators to add context to performance: an always hike model and an always cut model. Both of these perform the same policy action for every decision. The primary baseline used, however, is the "Last Decision" baseline, which predicts that each decision will be the same as the previous action (e.g., if the last decision was hike, predict hike), serving as a momentum baseline that tests the predictive power of persistence in our sample.

Evaluation Metrics:

To evaluate the effectiveness of each model, two metrics are used. For direction, the first metric is the standard accuracy, measuring how often each decision is predicted correctly. The second metric is balanced accuracy, where cumulative hike and cut predictions are weighed equally. The first metric for magnitude is Mean Absolute Error (MAE), or the sum of the absolute value of the prediction's residuals. Second is the Root Mean Squared Error (RMSE), which sums the squares of the prediction residuals.

■ Results

Directional Predictability:

We concluded that direction is highly predictable and systematic in the Federal Reserve's decision-making. The strongest predictive models we tested for directional accuracy were logistic regression and the Taylor-rule benchmark. As seen in Table 1, the Taylor Rule benchmark met or exceeded the machine learning models used. Additionally, it can be seen that the momentum baseline performs very well, which adheres to the concept of institutional inertia by indicating that policy momentum is central to policy direction in our sample. As the success shown would be unlikely if directional poli-

cy decisions were primarily discretionary, we have interpreted these results to mean that direction is governed by stable rules and inertia, with extra flexibility from machine learning models adding little further insight.

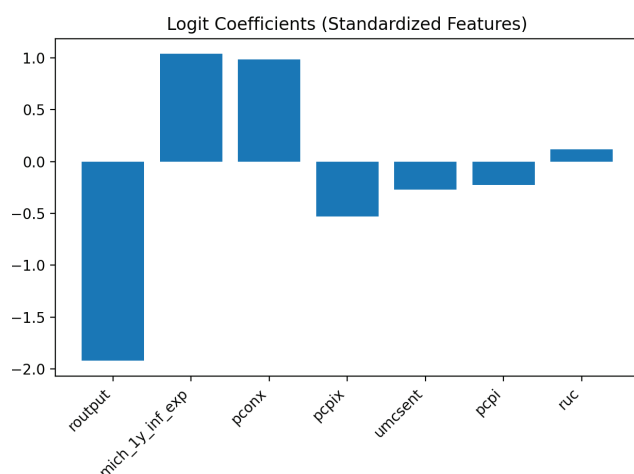


Figure 2: The relative importance of feature variables to the logistic regression model, with the output gap being the most important.

Figure 2 shows that the logistic regression model places the greatest importance on the output gap as a factor for predicting the direction of policy changes. This suggests that real economic activity plays a central role in the Federal Reserve's decision of whether to raise or lower interest rates.

Table 1: Directional prediction accuracy on decision events. The Taylor rule benchmark achieves the highest accuracy, indicating strong systematic behavior in policy direction.

Model	Accuracy	Balanced Accuracy	Notes
Always Hike	0.579	0.500	Naïve baseline
Always Cut	0.421	0.500	Naïve baseline
Last Decision	0.895	0.892	Momentum baseline
Logistic Regression	0.842	0.830	ML, interpretable
Random Forest	0.737	0.739	Nonlinear ML
Taylor Rule (Benchmark)	0.947	0.955	Structural benchmark

The strong direction-predicting performance of both the Taylor Rule Benchmark and the Last Decision Baseline suggests that the direction of the Federal Reserve's rate changes is not an impromptu judgment, but reflects a combination of macroeconomic rule-following and institutional policy momentum. This supports a view that even when the Federal Reserve exercises its power, the basic choice of hiking or cutting is highly constrained by clear and systematic factors like observable economic conditions and the current policy regime.

Magnitude Predictability:

In contrast, we found that magnitude is harder to predict with rule-based or systematic approaches than direction. As seen in Table 2, Ridge regression performs the best overall,

with superior accuracy to the more rigid and methodical Taylor Rule. As the Taylor rule's predictions are too smooth for the erraticism of decisions in magnitude, it underpredicts large moves even when accurate in direction. This underprediction is consistent with the selective discretion we identified in the magnitude of policy adjustments being episodic and concentrated during periods of uncertainty and stress. Additionally, the random forest regression model demonstrates limited additional improvement.

This loss in predictability seems to suggest a level of flexibility in how the Federal Reserve decides the extent of an adjustment, especially during periods of stress such as the COVID-19 pandemic, resulting in emergency easing followed by a post-pandemic inflation tightening cycle. We interpret this divergence as evidence that discretion matters less for whether the Federal Reserve hikes or cuts rates, and more for how aggressively it moves in that direction. Overall, we conclude that while directional decisions are likely largely systematic, magnitude decisions may be influenced more by selective discretion.

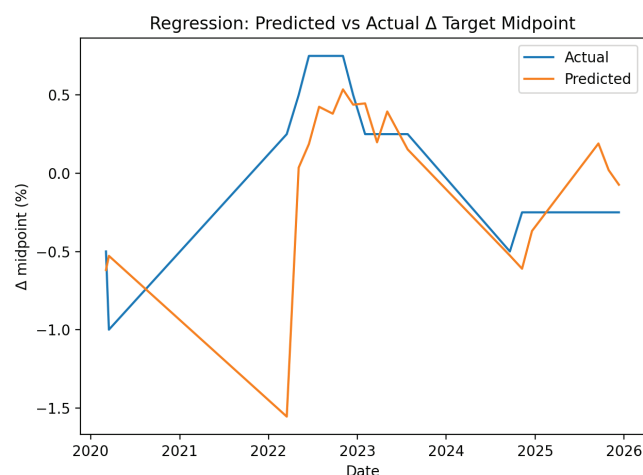


Figure 3: The discrepancy between regression-predicted rates and actual target rates.

Figure 3 shows that the predicted rate changes follow the general movements of actual policy, but fail to predict the larger deviations. This suggests that while the model can capture the broad direction of policy quite well, it fails to predict the exact size of rate adjustments, particularly during highly unusual or stressful periods where the most drastic changes occur.

Table 2: Magnitude prediction performance (Δ policy rate). Ridge Regression and Random Forest Regression outperform the Taylor Rule benchmark, suggesting less rule-like behavior.

Model	MAE	RMSE
Taylor Rule (Benchmark)	0.41	0.79
Ridge Regression	0.33	0.50
Random Forest (Regression)	0.37	0.47

The weaker magnitude-predicting performance of the Taylor Rule benchmark suggests that while systematic rules seem to capture the direction of Federal Reserve decisions well, they fail to accurately capture how aggressively it moves. This

distinction is important because policy magnitude is where central bankers may respond to financial stress, uncertainty, market expectations, or other crisis-specific risks that are complex and difficult to encode in a simple policy rule.

Taylor-Rule Benchmark:

When evaluated on our primary decision-event date dataset, the Taylor-rule benchmark performed with exceptionally high directional accuracy but performed relatively poorly in accurately predicting policy magnitude. As seen in Table 3, the Taylor rule's estimated coefficients indicate that policy responses are significantly impacted by output gap and core inflation, while the unemployment rate had minimal influence on predicted decisions. While not true structural policy reaction parameters, these coefficients give descriptive insights into deeper systematic decision-making within the realm of interest rate decision-making in the Federal Reserve.

Table 3: Estimated Taylor rule coefficients. Output gap and core inflation are weighted significantly compared to the unemployment rate.

Variable	Coefficient
Output gap	-0.96
Core inflation	0.86
Unemployment rate	-0.01

The strength of the output gap and core inflation coefficients reinforces evidence that the Taylor Rule benchmark is largely driven by these two major macroeconomic variables. The degree to which the coefficients of these variables are greater than the unemployment rate supports the idea that the Federal Reserve seems to act in a systematic way in response to transparent, broad macroeconomic fundamentals.

Regime and Cycle Analysis:

To further the notion of institutional inertia within federal interest rate policymaking, we split samples into time segments aligning with known policy cycles, such as the post-zero-lower-bound liftoff, as seen in Table 4. Within these regimes, policy behavior is nearly deterministic, with consistent direction. Errors only occur during transitory periods between regimes, which are inherently outside of the norm, suggesting that discretion is episodic in its impact. This uniformity suggests that discretion is episodic and used mainly during turning points. This also lends credibility to our momentum-based model success, as outside of outlying turning points, direction is almost entirely conforming to existing regime momentum. Overall, we find that regime persistence and institutional inertia play a central role in the Federal Reserve's interest rate decision-making.

Table 4: Model performance across monetary policy regimes. Remarkable direction consistency is held within regimes.

Regime	Period	N	% Hikes	Logit Accuracy	Baseline (Last Decision)
ZLB liftoff & hikes	2015–2018	9	100%	0.78	1.00
2019 easing	2019	3	0%	1.00	1.00
COVID emergency	2020	2	0%	1.00	1.00
Inflation hikes	2022–2023	11	100%	1.00	1.00
2024–2025 easing	2024–2025	6	0%	1.00	1.00

The regime results suggest that a great deal of the apparent predictability in monetary policy comes from persistence within policy cycles. Inflationary pressure, labor-market conditions, and output trends may lead the Fed into tightening and easing cycles, which continue into subsequent decisions in the same direction until another major regime shift occurs. This suggests that discretion may be most important not for ordinary decisions within a regime, but during crucial moments when the Fed decides to shift regimes.

Interpretability:

As seen from Table 3 and Table 5, the logistic and Taylor coefficients are extremely visible and interpretable, as the importance of each variable is evident in its coefficient. Our findings align with economic intuition of the influence of inflation and activity measures. The feature importance comparators of the random forest model also confirm these findings, as seen in Figure 4. By these models' success and interpretability, we conclude that policy is not truly opaque, and economic behavior is interpretable.

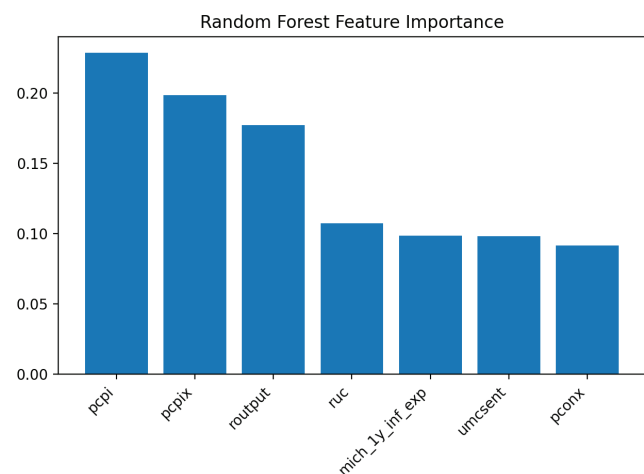


Figure 4: The relative importance of the features of the Random Forest model highlights the strength of the Consumer Price Index.

Figure 4 shows that CPI inflation, core CPI inflation, and the output gap are some of the most important prediction factors in the Random Forest model. This points to the idea that inflation and economic activity are key to the systematic portion of the Federal Reserve's decision-making.

Table 5: Logistic regression coefficients for policy direction. The output gap has the strongest predictive power in the logistic regression model.

Predictor	Coefficient	Coefficient Magnitude
Output Gap	-1.92	1.92
1-year inflation expectations	1.04	1.04
Core consumption inflation	0.98	0.98
Core CPI inflation	-0.53	0.53
Consumer Sentiment	-0.27	0.27
CPI inflation	-0.23	0.23
Unemployment rate	0.12	0.12

The output gap has the largest coefficient by magnitude, followed by inflation expectations and core consumption inflation. This table describes which variables were most important for predicting policy direction for our logistic regression model, and suggests that a mix of real economic activity and inflation-based measures plays a key role in the systematic component of Federal Reserve rate decisions.

Counterfactual Analysis:

The framework of our counterfactual evaluation to test the macroeconomic effects of systematic and discretionary policy is a stylized New Keynesian model.^{7,8} This model allows for a descriptive comparison between the actual policy path and a path implied by the Taylor-rule benchmark. While purely illustrative, this analysis aligns with our previous findings, suggesting that while the two paths only have small differences during stable periods, there are significant deviations during periods of stress. With this model as the basis for comparison, we find that discretion matters when concentrated, but over long periods of time, policy decisions of similar directional foundations through stable regimes result in largely similar outcomes.

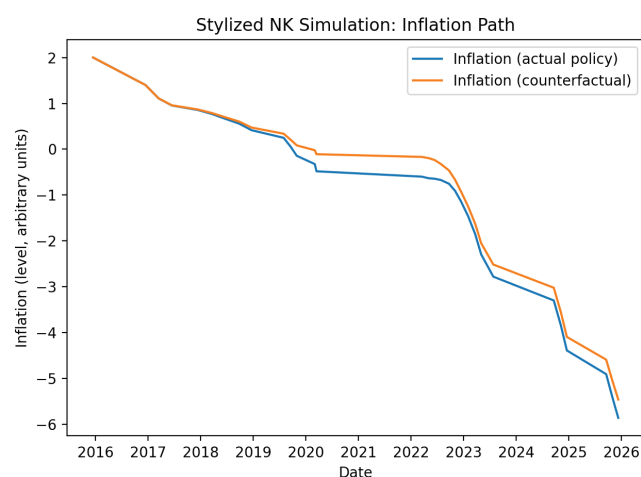


Figure 5: The predicted differences between actual policy and modeled policy over time demonstrate clear coherence during stable periods but larger differences during larger changes.

Figure 5 shows that actual and modeled policy paths derived from the stylized New Keynesian simulation are relatively similar during stable periods, but larger differences occur during periods of stress, causing greater divergence. This supports the conclusion that while systematic rules can explain much

of normal policy behavior, discretion becomes more important during crises and major regime shifts.

Discussion

These results reveal a nuanced view of Federal Reserve monetary policy. The strong performance of the Taylor Rule benchmark supports classic rules-based views of monetary policy associated with Taylor and later with Clarida, Galí, and Gertler, arguing that central bank behavior can be described through systematic responses to inflation and economic activity. As this paper utilizes real-time data, it extends Orphanides' critique of ex post economic analysis by claiming that real-time uncertainty matters,³ as well as prior research emphasis on the systematic nature of U.S. monetary policy.^{1,2} The relevant question is not whether policy appears systematic after future data revisions supply information unavailable to policymakers, but whether it remains predictable while restrained to data available at the time. Under these constraints, machine learning matches but does not beat rules in directional prediction modeling, highlighting the predictive strength of simple and interpretable rules, but the magnitude of rate changes is not nearly as well captured. This paper supports the view that directional monetary policy is well captured by rules, but that these rules may fail to fully capture the magnitude of policy adjustments.

A possible explanation for these findings is that the Federal Reserve's decisions are neither entirely mechanical nor discretionary. Simple policy rules may perform well in predicting the direction of decisions because they are highly related to the broad reaction function of the Federal Reserve. When inflationary pressure rises, or economic slack falls, the Fed will naturally tend to tighten, and in opposite conditions, it will tend to ease. From the success of the Last-Decision Baseline, it can be inferred that subsequent decisions tend to continue in the same direction until a major regime shift occurs. Machine learning offering limited improvement may suggest that much of the Fed's directional behavior is already largely captured by transparent macroeconomic relationships and institutional continuity.

On the other hand, simple rules' relatively weak ability to capture the magnitude of changes serves as possible evidence pointing to discretion playing a much larger role in the size and timing of adjustments as compared to the basic direction of policy. This reveals that central banks may behave simply at a high level while relying more on judgment when calibrating precise policy actions. This is sensible, as during crises, the Federal Reserve must judge whether or not to implement a more significant move or not for reasons ranging from the stabilization of markets, rapidly changing expectations, or even preservation of credibility. This offers a potential explanation for why the Taylor-rule benchmark correctly predicts the direction of policy, but underpredicts large moves.

These findings contribute to the rules-versus-discretion debate by suggesting that the dichotomy between rules and discretion may be less absolute than is often assumed. While the Federal Reserve appears to follow a rule-like pattern in general directional decisions, it may still preserve discretion

to determine the degree to which it should respond to economic conditions. In that sense, policy rules are shown to be useful not because they are a replacement for central bankers, but because they offer insights into understanding and evaluating policy behavior. This paper thus supports a middle ground view: rules dealing with broad macroeconomic indicators hold strong explanatory power over the systematic portion of monetary policy, but discretion in the size of an adjustment remains an important factor for uncertainty, institutional judgment, and conditions not covered by standard macroeconomic variables.

Future research could be put into comparison of the Federal Reserve's decision frameworks with those of other central banks, as well as more in-depth simulations of an automated central bank's effects on societal metrics.

■ Limitations

This study has several major limitations. Firstly, the dataset is extremely limited because FOMC decisions are sparse, and many meetings do not result in a change in target rate, which further limits the usable data points that prediction models can train and test on. This significant restriction of the amount of data for the models used limits the strength of statistical claims for accuracy. Secondly, the analysis only focuses on the selected set of macroeconomic indicators available to the public, but does not include qualitative information available to policymakers, such as market functioning, geopolitical risks, financial stability concerns, and internal deliberations. The lack of all potential factors in consideration makes it difficult to ascertain whether or not decisions are truly systematic or discretionary. Thirdly, the New Keynesian counterfactual simulations are not structural estimates of the full economy, but are merely illustrative. All in all, these major limitations mean that results should be treated as evidence about policy predictability and decision structure, and not a definitive model of how the Federal Reserve makes decisions.

■ Conclusion

This paper finds that the Federal Reserve's interest rate decisions are composed largely of two sub-decisions: the direction of rate change, which we thus refer to as "direction", and the extent of rate change, which we call "magnitude". To that end, based on our real-time data constraints, direction is largely rule-based while magnitude is comparatively discretionary and flexible, especially during periods of crisis or other turning points in economic regimes. This suggests that market expectations may be anchored in systematic directionality even during uncertainty around policy intensity. Machine learning models tested in this paper were able to match but not surpass structural benchmarks once real-time information constraints and regime persistence were imposed. This finding contributes to the macroeconomic policy rules-versus-discretion debate by adding the nuance of the components of policy action and their respective adherence to systematic decision-making, rather than overturning existing understandings. Because the sample size of active FOMC decisions is small and excludes potential qualitative internal deliberations, these findings should be in-

terpreted as evidence of predictability and structure in Federal Reserve decision-making rather than a complete model.

These results suggest future avenues of research, including similarities between the Federal Reserve and other central banks' decision-making and differences in the effects of changes in direction and magnitude on financial markets. Further exploration into different models, such as hybrid models incorporating rule-based and flexible mechanics, is also potentially interesting. Research into how Federal Reserve decision-making has changed, as well as comparisons between Federal Reserve behaviors towards different financial tools, could provide further nuance into the discussion surrounding its determinations.

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■ References

1. Taylor, J. B. Discretion versus policy rules in practice. *Carnegie-Rochester Conf. Ser. Public Policy* 1993, 39, 195–214.
2. Clarida, R.; Gali, J.; Gertler, M. Monetary policy rules and macroeconomic stability: Evidence and some theory. *Q. J. Econ.* 2000, 115 (1), 147–180.
3. Orphanides, A. Monetary policy rules based on real-time data. *Am. Econ. Rev.* 2001, 91 (4), 964–985.
4. Croushore, D.; Stark, T. A real-time data set for macroeconomists. *J. Macroecon.* 2001, 23 (2), 253–264.
5. Coulombe, P. G.; Leroux, M.; Stevanovic, D.; Surprenant, S. How is machine learning useful for macroeconomic forecasting? *J. Appl. Econom.* 2020, 35 (7), 920–964.
6. Korobilis, D. *Machine Learning Macroeconometrics: A Primer*; Essex Finance Center Working Paper No. 22666; University of Essex: Colchester, U.K., 2018. <https://ssrn.com/abstract=3246473>. (accessed 2026)
7. Christiano, L. J.; Eichenbaum, M.; Evans, C. Nominal rigidities and the dynamic effects of a shock to monetary policy. *J. Polit. Econ.* 2005, 113 (1), 1–45.
8. Smets, F.; Wouters, R. Shocks and frictions in U.S. business cycles: A Bayesian DSGE approach. *Am. Econ. Rev.* 2007, 97 (3), 586–606.
9. Bernanke, B. S. *Monetary Policy and the Housing Bubble*; Speech at the American Economic Association Meeting, Atlanta, GA, January 3, 2010. <https://www.federalreserve.gov/newsevents/speech/files/bernanke20100103a.pdf> (accessed 2026).
10. Blinder, A. S.; Reis, R. Understanding the Greenspan standard. *Brookings Pap. Econ. Act.* 2005, 2005 (2), 11–96.
11. Athey, S. *The Impact of Machine Learning on Economics*; NBER Working Paper No. 24449; National Bureau of Economic Research: Cambridge, MA, 2018. <https://www.nber.org/books-and-chapters/economics-artificial-intelligence-agenda/impact-machine-learning-economics> (accessed 2026).
12. Orphanides, A.; van Norden, S. The unreliability of output-gap estimates in real time. *Rev. Econ. Stat.* 2002, 84 (4), 569–583.
13. Taylor, J. B. *Housing and Monetary Policy*; NBER Working Paper No. 13682; National Bureau of Economic Research: Cambridge, MA, 2007.
14. Wieland, V.; Wolters, M. The diversity of forecasts from macroeconomic models. *Econ. Policy* 2011, 26 (65), 1–54.

15. Federal Open Market Committee. *Minutes of the Federal Open Market Committee, December 15–16, 2015*; Board of Governors of the Federal Reserve System: Washington, DC, 2016. <https://www.federalreserve.gov/monetarypolicy/files/fomcminutes20151216.pdf> (accessed 2026).
16. Federal Reserve Bank of Philadelphia. *Real-Time Data Set for Macroeconomists*. <https://www.philadelphiafed.org/surveys-and-data/real-time-data-research> (accessed 2026).
17. Federal Reserve Bank of St. Louis. *Federal Reserve Economic Data (FRED)*. <https://fred.stlouisfed.org/> (accessed 2026).
18. Federal Reserve Bank of St. Louis. *ALFRED: Archival Federal Reserve Economic Data*. <https://alfred.stlouisfed.org/> (accessed 2026).
19. Federal Reserve Board. *FOMC Statements, Minutes, and Transcripts*. <https://www.federalreserve.gov/monetarypolicy/fomc-calendars.htm> (accessed 2026).
20. University of Michigan. *Survey of Consumers*. <https://data.sca.isr.umich.edu/> (accessed 2026).

■ Author

Zachary Wong is a student at Walter Payton College Prep in Chicago, Illinois. His research interests include macroeconomic policy and machine learning applications in economics. He intends to pursue economics and computer science at the university level.

■ Appendix

Random Forest Feature Importance. The Consumer Price Index holds the strongest importance in the Random Forest model.

Predictor	Importance
CPI inflation	0.229
Core CPI inflation	0.198
Output gap	0.177
Unemployment rate	0.108
Inflation expectations	0.099
Consumer sentiment	0.098
Core consumption inflation	0.092