

BEYOND THE INVERSION
A Novel Approach on the Structural Decomposition of the Term Spread

by

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Abstract

This study reveals that the term spread's predictive power is fundamentally state-dependent, critically shaped by the structural origin of macro-financial shocks. Yield curve inversions driven by monetary tightening consistently precede output contractions, confirming their diagnostic value. However, flattenings induced by inflation shocks generate misleading signals—false positives—whereas uncertainty shocks suppress real activity without altering the slope, producing false negatives. Structural variance decompositions show that monetary policy is the dominant driver of the spread, while uncertainty primarily influences output fluctuations. Crucially, regime-dependent probit models demonstrate that the term spread forecasts recessions far more effectively in low-uncertainty environments. These findings underscore the limitations of reduced-form approaches and advocate for structurally grounded interpretations of yield curve dynamics, especially in eras of elevated uncertainty and policy regime shifts.

I am especially grateful to Professor Álvaro Escribano for his inspiring teaching at UC3M and for shaping my structural thinking. Naturally, all remaining errors and conclusions are my sole responsibility.

1. Introduction

The slope of the yield curve — typically measured as the difference between long-term and short-term interest rates — has long been recognized as one of the most reliable predictors of future economic activity. An inverted yield curve has preceded most U.S. recessions since the 1960s and is often interpreted as a signal of deteriorating macroeconomic conditions. However, recent episodes have challenged the unconditional reliability of this indicator. In particular, there have been instances in which the yield curve has inverted without being followed by a recession, raising important questions about the sources of its predictive power — and its limitations.

A key insight proposed by Bauer and Mertens (2018) is that the yield spread reflects not just expectations of future short-term interest rates, but **also time-varying risk premia**. As a result, movements in the term spread may be driven by factors unrelated to the macroeconomic outlook—such as shifts in inflation expectations, monetary policy credibility, or investor sentiment. For instance, a flattening or inversion of the yield curve may occur not because the economy is weakening, but because investors demand a higher premium to hold long-term bonds due to concerns about inflation risk. These distortions, sometimes referred to in the literature as “**inflation scare shocks**,” can lead to false positives in recession prediction.

Earlier contributions by Smets and Tsatsaronis (1997) also emphasized the importance of understanding the structural sources of term spread movements. Using a structural VAR approach, they demonstrated that the yield curve embeds information not only about future economic activity but also about the behavior of monetary policy and inflation expectations. Their findings highlight that a purely reduced-form interpretation of the spread can be misleading unless one accounts for its **underlying macro-financial drivers**.

This observation motivates the use of a structural vector autoregressive (SVAR) model to decompose movements in the yield spread into their underlying macroeconomic sources. By identifying **structural shocks** — within a theoretically grounded framework, it becomes possible to determine whether an inversion of the yield curve is signaling a genuine economic slowdown or simply reflecting changes in investor behavior or expectations.

The present paper builds directly on this framework but proposes an important extension. In particular, we introduce the **Economic Policy Uncertainty (EPU)** index as an additional variable in the SVAR system. This innovation responds to two key developments. First, there is growing empirical evidence that uncertainty shocks — particularly those arising from political, regulatory, or geopolitical events — can significantly influence financial conditions, investment, and real activity, **independently of traditional macroeconomic channels**. Second, many of the recent deviations between yield curve signals and subsequent economic outcomes have coincided with periods of heightened policy uncertainty.

By explicitly modeling uncertainty as a structural driver of the term spread and macroeconomic variables, we aim to **refine the interpretation of yield curve signals**. Specifically, our approach allows us to assess whether part of the yield curve's predictive power is being attenuated or distorted by uncertainty-related risk premia and flight to safety behaviors, and whether this accounts for recent predictive ambiguities.

2 SVAR MODEL

2.1 Econometric Identification Strategy and Theoretical Framework

Our empirical approach is based on an identified Structural Vector Autoregressive (SVAR) model. This framework allows us to isolate orthogonal structural shocks from observed macro-financial dynamics using a recursive (**Cholesky**) **identification scheme**. To justify this structure, we draw on standard aggregate supply-demand models and forward-looking monetary theory, as in Fuhrer and Moore (1995), Svensson (1996), and Smets and Tsatsaronis (1997).

$$x_t = \begin{bmatrix} \text{EPU}_t \\ y_t \\ \pi_t \\ i_t \\ s_t \end{bmatrix} \quad \varepsilon_t = \begin{bmatrix} \varepsilon_t^{\text{EPU}} \\ \varepsilon_t^y \\ \varepsilon_t^\pi \\ \varepsilon_t^i \\ \varepsilon_t^s \end{bmatrix} \quad A_0^{-1} = \begin{bmatrix} * & 0 & 0 & 0 & 0 \\ * & * & 0 & 0 & 0 \\ * & * & * & 0 & 0 \\ * & * & * & * & 0 \\ * & * & * & * & * \end{bmatrix} \quad u_t = A_0^{-1} \varepsilon_t$$

2.1.1 Theoretical Foundations

The SVAR framework is grounded in a stylized macroeconomic model comprising five canonical relationships:

1. **Aggregate Supply (AS)** – $\bar{y}_t = \bar{y}_{t-1} + \eta_t^s$
(*Potential output follows a random walk, capturing supply shocks.*)
2. **IS Curve** – $y_t = \beta_1 y_{t-1} + \beta_2 y_{t-2} + (1 - \beta_1 - \beta_2) \bar{y}_{t-1} - \beta_4 R_{t-1} + \eta_t^d$
(*Output depends on past values and negatively on the real interest rate, reflecting intertemporal substitution.*)
3. **Monetary Policy Rule (Taylor-type)** – $i_t = \gamma_1(i_{t-1} - \pi_{t-1}) + \gamma_2 \pi_t + \gamma_3(y_t - \bar{y}_t) + \eta_t^p$
(*The central bank sets short-term nominal rates responding to inflation and the output gap, with inertia.*)
4. **Fisher Equation** – $R_t = \rho_t + \frac{1}{N} \sum_{i=0}^{N-1} E_t \pi_{t+i+1} + \xi_t$
(*Long-term real rates reflect expected future inflation and may embed inflation scare distortions.*)
5. **Expectations Hypothesis** – $R_t = \frac{1}{N} \sum_{i=0}^{N-1} E_t i_{t+i}$
(*Nominal long-term rates incorporate expectations of future short-term policy rates.*)

Together, these equations provide a structural foundation to disentangle supply, demand, policy, and expectation-driven shocks within the SVAR model.

2.1.2 Identification Strategy and Variable Ordering

Following the structural identification approach proposed by Smets and Tsatsaronis (1997), we order the variables in our SVAR model based on standard macroeconomic theory regarding the contemporaneous interaction between real activity, prices, monetary policy, and financial markets.

First, **real output growth (Y)** is placed at the top of the ordering. This reflects the notion that real economic activity is relatively slow-moving, responding only gradually to shocks. Investment, consumption, and production decisions are subject to implementation lags, making it unlikely that output reacts contemporaneously to changes in monetary policy or financial conditions within the same quarter. This assumption aligns with standard New Keynesian models and dynamic stochastic general equilibrium (DSGE) frameworks.

Second, we place **inflation (P)**. While inflation can respond quickly to output shocks, especially through demand pressures, it is less sensitive to monetary policy or financial variables within a quarter due to nominal rigidities and slow price adjustments, as described in the literature on sticky prices (e.g., Calvo pricing models).

Third, we include the **short-term interest rate (R)**, representing monetary policy actions. Monetary policy is assumed to react contemporaneously to both output and inflation, consistent with Taylor-type policy rules, where central banks adjust policy rates in response to deviations of inflation and output from their targets.

Fourth, we position the **term spread (S)**. Financial markets, and particularly bond markets, are highly responsive to new information. The term spread is assumed to react contemporaneously to shocks in output, inflation, and monetary policy, incorporating expectations about future economic conditions and risk premia almost instantaneously.

Finally, to extend the original model, we introduce the **Economic Policy Uncertainty (EPU) index** as an additional variable, placed first in the Cholesky ordering. This choice is motivated by both economic theory and empirical evidence.

From a theoretical perspective, uncertainty shocks, particularly those related to economic policy, are considered **exogenous at the quarterly frequency** because they predominantly arise from political, institutional, or exogenous global events, rather than being immediate outcomes of macroeconomic fundamentals such as output, inflation, or monetary policy. For instance, elections, unexpected regulatory changes, international conflicts, and legal uncertainties can lead to abrupt shifts in agents' expectations without requiring contemporaneous changes in measurable economic indicators.

1. Empirically, previous studies have consistently treated uncertainty shocks as exogenous within structural models. Bloom (2009) models' uncertainty as a shock that affects investment and hiring decisions, but which is itself largely immune to contemporaneous macroeconomic developments. Ludvigson, Ma, and Ng (2021) similarly argue that uncertainty is best captured as an information-based shock that influences economic outcomes but is not itself the immediate product of endogenous macro fluctuations.

Placing the EPU first allows its innovations to contemporaneously affect real activity, inflation, monetary policy, and the yield curve, while preventing reverse causality within the same period. This ensures that the estimated uncertainty shock reflects **exogenous informational disturbances**, rather than endogenous reactions to economic conditions. Given the growing role of uncertainty in modern macro-financial dynamics, incorporating the EPU index provides a more comprehensive and realistic depiction of the structural forces driving movements in the yield spread.

2.2 Unit roots analysis

All variables used in the SVAR model — including the EPU index, interest rates, spreads, output growth, and inflation — are included in levels, consistent with the established literature (e.g., Bloom, 2009; Ludvigson, Ma, and Ng, 2021). Augmented Dickey-Fuller tests confirm that these series, while persistent, do not exhibit explosive behavior, allowing valid inference without differencing. Importantly, real output and the price level are not included in levels but are transformed into their annualized growth rate and inflation rate, respectively. This treatment ensures stationarity and aligns with the standard macro-financial SVAR specification used in Christiano, Eichenbaum, and Evans (1999), where cyclical dynamics are captured through first differences of real variables. The resulting system reflects macroeconomic interactions at business-cycle frequency while preserving structural interpretability. Overall, the specification balances theoretical coherence with empirical robustness, ensuring the meaningful identification of uncertainty and policy shocks.

2.3 Residual Diagnostics

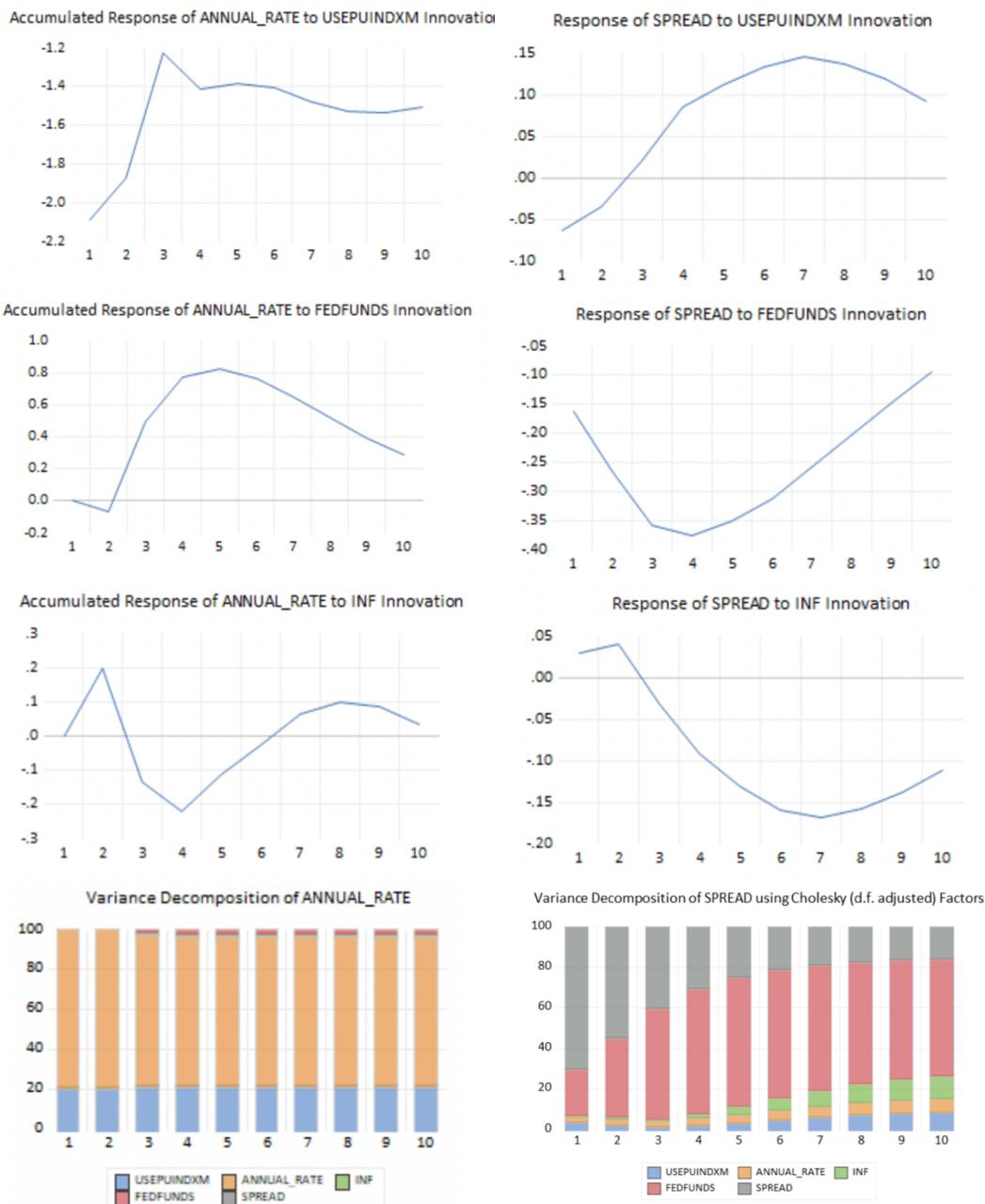
To validate the robustness of the SVAR specification, we conducted standard residual diagnostics including tests for autocorrelation, heteroskedasticity, and model stability. Autocorrelation was assessed using both Portmanteau and LM tests. While the Portmanteau test indicated some residual correlation at lower lags, this effect diminished at higher orders, and the LM test consistently failed to reject the null hypothesis of no serial correlation beyond lag 3.

Correlogram analysis further supported this conclusion, as residual autocorrelations remained largely within the confidence bounds and showed no systematic patterns. Regarding stability, all inverse roots of the characteristic AR polynomial were contained within the unit circle, satisfying the condition for dynamic stability, and justifying the use of impulse response functions and forecast error variance decompositions. However, diagnostic testing revealed strong evidence of residual heteroskedasticity across the system. The joint null of homoskedasticity was decisively rejected. While such heteroskedasticity does not compromise the point estimates of structural shocks or dynamic responses, it can lead to unreliable inference through biased standard errors and misestimated confidence bands. This is a known limitation in macro-financial models, where residual variance often fluctuates with financial conditions or policy regimes. Overall, the SVAR residuals meet the essential requirements for structural interpretation, though future research may benefit from incorporating heteroskedasticity-robust inference methods or generalized impulse response functions to enhance statistical validity.

2.4 Impulse Response Analysis

This section analyzes the dynamic effects of structural shocks on key macro-financial variables, with particular emphasis on understanding the structural foundations of the term spread's predictive power. Cumulative impulse responses are reported for variables expressed in growth rates, while non-cumulative responses are used for variables in levels. Rather than presenting all possible shock-response combinations, the analysis focuses selectively on those responses that provide direct insight into the spread's ability to anticipate real economic fluctuations.

Responses to Cholesky one S.D. innovations



2.4.1 Response to a Monetary Policy Shock: A source of true positives

The response to a monetary policy shock illustrates the classical mechanism through which the yield curve embeds forward-looking information about economic conditions. An unexpected tightening of monetary policy, captured by an increase in the Federal Funds Rate, leads to a clear flattening of the yield curve as short-term rates rise more than long-term rates. This mechanical steepness adjustment is consistent with standard theory, in which policy-induced inversions are interpreted as recessionary signals.

However, the output response to such a shock in the current sample is relatively mild and short-lived, with the cumulative effect losing statistical precision beyond the medium term. While this deviates from textbook expectations of persistent and significant real contractions, it does not invalidate the predictive content of the spread. Rather, it reflects changes in the broader macro-financial environment over recent decades that may have weakened the transmission from monetary policy to real activity.

In particular, the proximity to the **effective lower bound (ELB)** in recent decades—especially post-2008 and during the pandemic—has likely weakened the transmission of monetary shocks. When nominal rates are near zero, central banks face tighter constraints, and long-term expectations often remain anchored by forward guidance or credibility effects. As a result, even if short-term rates increase, the contractionary impulse on real activity may be limited. These dynamics suggest that while monetary policy still shapes the spread, its predictive power for output weakens in low-rate regimes and must be interpreted within a **regime-sensitive framework**.

2.4.2 Response to an Inflation Shock: A Source of False Positives

Inflation shocks, modeled here as standard cost-push disturbances, also lead to a significant flattening of the yield curve, as captured by a strong decline in the term spread. This response likely reflects a monetary policy reaction: short-term rates rise as central banks respond to inflation, while long-term rates remain relatively stable, causing the curve to flatten. However, the corresponding output response is relatively muted and transitory. The cumulative effect on real growth fades over time, indicating that such shocks do not induce sustained contractions in activity. While not pure “inflation scare” in the sense of Smets and Tsatsaronis (1997), This decoupling between the spread and real output highlights a key limitation: when yield curve flattening stems from **inflation-driven policy** responses rather than underlying demand weakness, the spread may falsely signal recession risks — a potential source of **false positives**.

2.4.3 Response to an Uncertainty Shock: A source of false negatives

The most critical divergence appears in the response to uncertainty shocks. Following an increase in economic policy uncertainty, real output contracts sharply and persistently, consistent with theories emphasizing the role of **precautionary behavior** and investment delays. Yet, paradoxically, the term spread does not respond accordingly. In fact, it shows little movement and may even steepen temporarily. This dynamic reflects a **parallel downward shift** in the yield curve. In response to increased uncertainty, monetary authorities ease policy, reducing short-term interest rates. At the same time, investor **flight to safety** exerts downward pressure on long-term yields.

Since both ends of the curve fall in tandem, the slope remains broadly unchanged—or even increases—thereby muting the signal.

Initially, as we see in the **IRF**'s the spread may decline slightly, hinting at an economic slowdown. This early movement could reflect a flight to safety dynamic, putting downward pressure on long-term yields and beginning to flatten the curve. However, as monetary authorities respond by easing policy and cutting short-term interest rates, the initial signal begins to fade. The resulting policy-induced decline at the short end can dominate the yield curve's slope, especially if long-term rates begin to stabilize.

Moreover, once markets begin to calm and the acute phase of uncertainty passes, a counteracting mechanism may emerge; rising uncertainty or risk aversion can lead investors to demand higher term premia as compensation for future volatility. This upward pressure on long-term yields may partially offset the initial flight-to-safety effect, contributing to a steepening of the curve. As a result, recessions driven by uncertainty shocks may unfold without being flagged by an inversion, giving rise to **false negatives** in yield curve-based forecasts.

This interpretation is reinforced by the **variance decomposition** results: uncertainty shocks explain a **substantial share of the forecast error variance in output**, particularly over medium horizons, but contribute very little to the spread's variation. This disconnect highlights the diagnostic limitation of the spread in the presence of uncertainty: since uncertainty shocks trigger simultaneous downward movements in both ends of the curve, the spread does not respond, even though real economic conditions deteriorate meaningfully. In other words, **uncertainty has real effects, but does not “register” in the spread**, precisely because it activates offsetting responses across the yield curve.

2.4.4 Integrated Interpretation

Taken together, the impulse response analysis reveals that the term spread is a **conditionally predictive** indicator. Its reliability hinges on the type of shocks driving the economy. When the spread flattens following a monetary policy tightening, it accurately anticipates recessions. However, if the flattening arises from inflation shocks, the signal becomes noisier and prone to **false positives**, as policy-induced inversions may occur without underlying demand weakness. Conversely, **uncertainty shocks** often lead to sharp output contractions without affecting the spread, increasing the risk of **false negatives**.

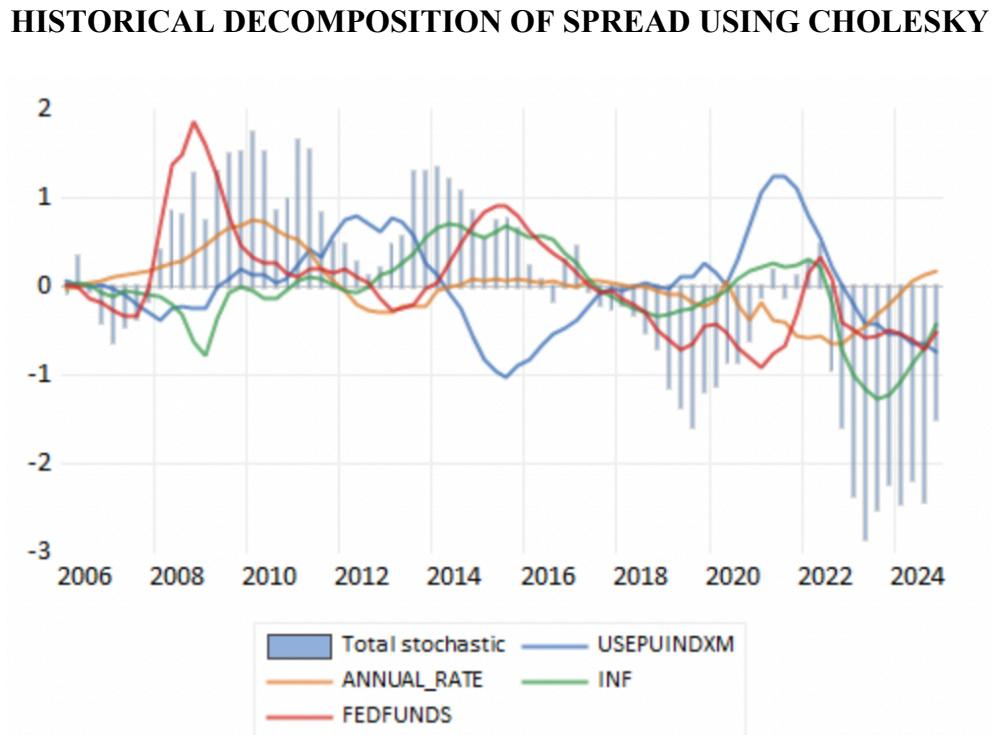
2. Theoretically, Uncertainty shocks can generate complex yield curve dynamics. Their net effect on the term spread depends on the interplay between safe-haven flows, policy easing, and risk premia adjustments. While initial reactions may cause a slight flattening due to flight to safety, our SVAR results suggest that central bank easing and risk-premia-induced upward pressure on long-term yields can quickly offset this, leaving the spread broadly unchanged—or even steepened. This undermines the curve's ability to anticipate downturns driven by uncertainty, giving rise to false negatives.

2.5 Robustness Check: Sensitivity to Cholesky Ordering

To test the robustness of the identification strategy, we alter the position of the Economic Policy Uncertainty (EPU) index within the Cholesky decomposition. Our baseline specification treats EPU as the most exogenous variable, we compare this with two alternatives: one where it is partially endogenous (ordered after output), and another where it is fully endogenous (ordered last). Across all specifications, the impulse responses remain stable: uncertainty shocks consistently cause output to contract, while the term spread remains unresponsive. This confirms that the core conclusion—uncertainty-driven recessions can occur without yield curve inversion—is **not dependent on identification assumptions**. This reinforces the structural validity of our results and supports the interpretation of the term spread as a conditionally predictive indicator.

2.6 Structural Origins of Yield Curve Inversions: Evidence from Decompositions

To properly evaluate the informational content of the term spread, this section provides a structural interpretation of its historical dynamics using the SVAR decomposition presented below. The panel illustrates the contributions of four orthogonal shocks—monetary policy, inflation, economic activity, and uncertainty—to the evolution of the spread between 2006 and 2024. Together, these layers offer a structural lens through which to understand whether the spread is sending a valid signal and how different forces interact to shape its slope.



2.6.1 Historical Decomposition: What Drives Yield Spread Movements?

In the lead-up to the Global Financial Crisis (2007–2008), the spread inverted in a manner that is both consistent with theory and clearly interpretable through the SVAR framework. The decomposition indicates that monetary policy shocks were the primary drivers of the inversion, as the Federal Reserve raised short-term rates aggressively in an effort to contain overheating risks. This pushed the short end of the curve upward, while long-term yields remained relatively stable or even declined marginally in anticipation of weaker future growth. Inflation and uncertainty shocks made negligible contributions during this phase. The term spread thus reflected genuine policy-driven dynamics. Importantly, uncertainty did not counteract the tightening; it remained low and played no significant role. The signal was therefore clean, timely, and structurally valid—a textbook example of a **true positive**.

By contrast, the brief inversion observed in mid-2019 was not merely a technical anomaly, but rather a structurally muted signal. The Federal Reserve had paused its tightening cycle and begun to ease, applying moderate downward pressure on short-term rates. Long-term yields also declined, but at a slower pace than expected, despite growing concerns over global trade tensions and signs of weakening activity. The historical decomposition provides clarity: monetary policy shocks (red line) contributed modestly to the inversion, while uncertainty shocks (blue line) exerted a slight **offsetting influence** on the spread.

Crucially, the nature of the uncertainty shock in 2019 differed from classical risk aversion episodes. Rather than triggering a strong flight to safety, uncertainty acted by **raising the term premium**—that is, increasing the compensation investors demanded for holding long-duration assets amid geopolitical instability. This put **upward pressure on long-term yields**, partially counteracting the flight to safety and the Fed’s easing at the short end, **dampening the curve’s inversion**. In this light, the 2019 episode should not be seen as a false positive, but as an **understated true signal**—muted by structural forces that distorted the slope.

The COVID-19 crisis in early 2020, by contrast, represents a clear inflection point. In this case, monetary policy shocks and uncertainty shocks moved in opposite directions. The Federal Reserve cut rates aggressively to the zero lower bound, compressing the short end, while extreme uncertainty drove investors toward long-term government bonds, pulling down the long end via a sharp **flight-to-safety dynamic**. The historical decomposition captures this as a pair of opposing forces—each powerful—whose **net effect** on the spread was modest, despite severe real deterioration. Structurally, this episode constitutes a **false negative**, where the curve failed to invert meaningfully—not due to the absence of shocks, but because those shocks were **mutually offsetting**, suppressing the spread’s ability to signal the true extent of the macroeconomic deterioration.

3. Although both episodes are characterized by elevated levels of economic uncertainty, the nature and transmission of that uncertainty differ significantly. In 2019, uncertainty increased gradually and was largely endogenous to the policy environment—driven by trade tensions and geopolitical developments. This prompted a repricing of long-term risk, leading to higher term premia and thus exerting upward pressure on long-term yields. In contrast, the shock of early 2020 was abrupt, exogenous, and systemic, triggered by the COVID-19 outbreak. The resulting spike in perceived risk produced a flight-to-safety dynamic, with investors reallocating aggressively into long-duration government securities, thereby compressing the long end of the yield curve. Accordingly, although both episodes reflect uncertainty shocks, they do so through distinct macro-financial mechanisms, each with divergent effects on the term structure.

A very different configuration emerges between 2022 and 2024. In response to persistent inflationary pressures following the post-pandemic recovery, the Federal Reserve embarked on an aggressive tightening cycle. The short-term interest rate rose steeply, generating powerful monetary policy shocks that the decomposition identifies as a driver of the spread inversion. Inflation shocks and uncertainty shocks also contributed, though in structurally distinct ways:

Inflation shocks (green line) made the largest downward contribution to the spread between 2022 and 2024. Rather than signaling weak demand directly, this effect is better interpreted as a reflection of disinflationary expectations. As the Federal Reserve's tightening stance gained credibility, markets began to anticipate that inflation would fall over the medium term. This reduced the inflation risk premium embedded in long-term yields, exerting downward pressure on the long end of the curve and reinforcing the inversion.

Uncertainty shocks (blue line) Although less extreme than during the COVID peak, led to safe-haven flows into long-duration bonds, which further compressed the long end of the curve. This is critical: unlike in 2020, uncertainty did not act symmetrically on both ends of the curve. Instead, it reinforced the policy-driven inversion by lowering long-term yields.

This asymmetry is key to interpreting the signal. Even in the absence of elevated uncertainty, the spread would likely have remained negative due to monetary tightening. However, the co-movement of risk sentiment and policy action amplified the slope inversion, making this episode a structurally grounded signal—**possibly a true positive reinforced by uncertainty**. In contrast to 2020's false negative and 2019's muted true signal, the 2022–2024 configuration shows that uncertainty can also sharpen the informational content of the yield curve.

Taken together, these findings underscore the importance of structurally decomposing the yield curve. Monetary policy remains a consistent source of valid predictive power, but the role of uncertainty is more nuanced. It may **amplify** (as in 2022–2024), **cancel** (as in 2020), or **distort** (as in 2019) the signal—Only by distinguishing which side of the curve each shock is affecting—and whether it supports or contradicts the signal—can the spread be reliably interpreted as a forward-looking macroeconomic indicator.

3. Regime-Specific Probit Analysis: Yield Spread Predictability under Uncertainty

To complement the structural analysis, this section estimates a **binary probit model** to explore whether the predictive content of the term spread varies with the prevailing level of economic policy uncertainty. The dependent variable is a binary recession indicator equal to one if a recession occurs within the next twelve months.

$$P(\text{Recession}_{t+12} = 1) = \Phi(\beta_0 + \beta_1 \cdot \text{Spread}_{t+12})$$

4. Given the structural nature and objectives of this thesis, the probit model is not meant to serve as a standalone forecasting tool but rather as a complementary robustness check. The changes in coefficients across uncertainty regimes provide strong evidence for the conditional predictability of the yield spread. Further econometric refinements—such as white noise or heteroscedasticity tests—are not strictly necessary for the narrative and analytical purposes of this work.

A regime-switching framework is employed, dividing the sample based on the EPU index. In the **low-uncertainty regime**, macro-financial signals tend to be transmitted more transparently, allowing the yield spread to retain a stronger informational role. In contrast, under **high uncertainty regimes**, simultaneous movements in short- and long-term interest rates may blur or mute the signal embedded in the slope of the yield curve.

Empirical results reveal that the yield spread remains a statistically significant predictor of future recessions across both regimes ($p < 0.01$). However, its predictive power is not uniform. During periods of low uncertainty, the estimated coefficient is higher ($\beta = 0.55$), and the model exhibits better fit (McFadden's $R^2 = 0.15$), suggesting clearer signal transmission. Under high uncertainty, although the spread coefficient remains statistically significant ($\beta = 0.38$), the model fit declines ($R^2 = 0.09$).

These results reinforce the insight from the SVAR and historical decomposition: **high uncertainty reduces the signal-to-noise ratio** of the spread. Some recessions may thus occur with limited warning from the curve (*false negatives*), while some inversions during inflation-driven policy tightening may overstate recession risks (*false positives*). These findings highlight the necessity of interpreting yield curve movements through the lens of prevailing uncertainty conditions, rather than treating them as mechanically recession predictive.

4. Conclusion

This thesis demonstrates that the yield curve's predictive power is fundamentally conditional, not mechanical. By structurally decomposing the drivers of the term spread and accounting for regime-dependent uncertainty, the analysis reveals that the yield curve may invert for very different reasons — not all of which point to recession.

Uncertainty emerges as a new interpretive lens. During high-uncertainty periods, macro-financial signals become blurred: policy easing, and flight-to-safety behavior may compress the curve symmetrically, masking underlying macroeconomic fragilities. In these contexts, the spread loses its clarity — and with it, part of its predictive content. By explicitly integrating uncertainty into the structural decomposition this framework refines the interpretations of the slope-based signals.

Together, the SVAR and regime-specific probit results call for a rethinking of how we read the yield curve. They urge analysts, policymakers, and investors to reconsider simplistic rule-of-thumb interpretations and embrace a structurally informed framework — one that looks beyond the inversion, and into the forces that shape it.

In an era of heightened uncertainty and shifting regimes, understanding why the yield curve inverts is as crucial as the inversion itself.

SUPPLEMENTARY APPENDIX

Null Hypothesis: USEPUINDXM has a unit root

Exogenous: Constant

Lag Length: 0 (Automatic - based on SIC, maxlag=13)

	t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic	-3.488014	0.0097
Test critical values:		
1% level	-3.477835	
5% level	-2.882279	
10% level	-2.577908	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: INF has a unit root

Exogenous: Constant

Lag Length: 0 (Automatic - based on SIC, maxlag=13)

	t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic	-8.494260	0.0000
Test critical values:		
1% level	-3.477835	
5% level	-2.882279	
10% level	-2.577908	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: SPREAD has a unit root

Exogenous: Constant

Lag Length: 1 (Automatic - based on SIC, maxlag=13)

	t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic	-3.010720	0.0363
Test critical values:		
1% level	-3.478189	
5% level	-2.882433	
10% level	-2.577990	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: ANNUAL_RATE has a unit root

Exogenous: Constant

Lag Length: 0 (Automatic - based on SIC, maxlag=13)

	t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic	-13.65229	0.0000
Test critical values:		
1% level	-3.477835	
5% level	-2.882279	
10% level	-2.577908	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: FEDFUNDS has a unit root

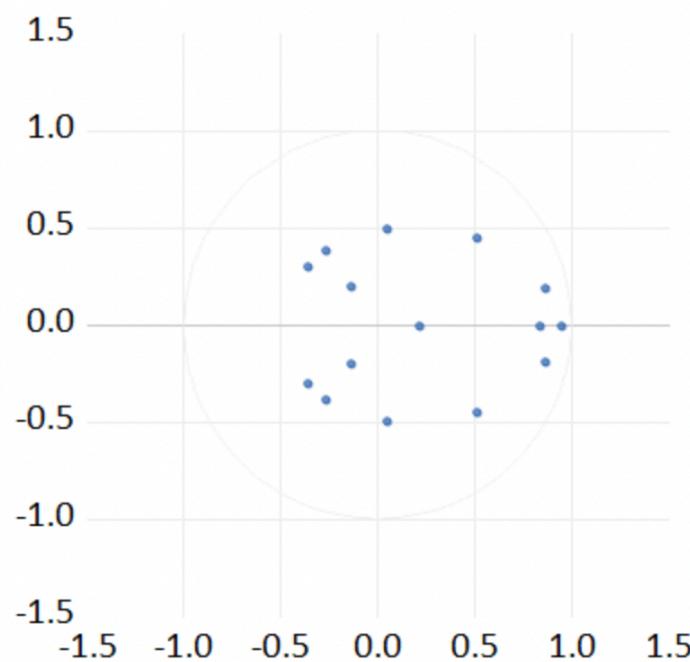
Exogenous: Constant

Lag Length: 1 (Automatic - based on SIC, maxlag=13)

	t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic	-3.363538	0.0140
Test critical values:		
1% level	-3.478189	
5% level	-2.882433	
10% level	-2.577990	

*MacKinnon (1996) one-sided p-values.

Inverse Roots of AR Characteristic Polynomial



VAR Residual Portmanteau Tests for Autocorrelations
 Null Hypothesis: No residual autocorrelations up to lag h
 Date: 04/30/25 Time: 11:08
 Sample: 1990Q1 2024Q4
 Included observations: 137

Lags	Q-Stat	Prob.*	Adj Q-Stat	Prob.*	df
1	2.222970	---	2.239315	---	---
2	7.947543	---	8.048697	---	---
3	19.47914	---	19.83846	---	---
4	40.12603	0.0283	41.10631	0.0224	25
5	64.21027	0.0853	66.10284	0.0631	50
6	87.27102	0.1573	90.21980	0.1110	75
7	117.2675	0.1144	121.8315	0.0681	100
8	146.1514	0.0950	152.5066	0.0477	125
9	171.1739	0.1137	179.2885	0.0516	150
10	196.2093	0.1300	206.2952	0.0529	175
11	210.6297	0.2893	221.9745	0.1370	200
12	230.7586	0.3819	244.0358	0.1829	225

*Test is valid only for lags larger than the VAR lag order.
 df is degrees of freedom for (approximate) chi-square distribution

VAR Residual Serial Correlation LM Tests

Date: 04/30/25 Time: 11:08
 Sample: 1990Q1 2024Q4
 Included observations: 137

Null hypothesis: No serial correlation at lag h

Lag	LRE* stat	df	Prob.	Rao F-stat	df	Prob.
1	21.80702	25	0.6469	0.870844	(25, 417.6)	0.6472
2	34.79256	25	0.0920	1.410830	(25, 417.6)	0.0922
3	26.23526	25	0.3951	1.053153	(25, 417.6)	0.3955
4	22.75923	25	0.5916	0.909888	(25, 417.6)	0.5920
5	27.16725	25	0.3476	1.091763	(25, 417.6)	0.3480
6	23.40212	25	0.5541	0.936297	(25, 417.6)	0.5545
7	31.72207	25	0.1662	1.281669	(25, 417.6)	0.1665
8	31.43250	25	0.1751	1.269535	(25, 417.6)	0.1754
9	25.74820	25	0.4211	1.033009	(25, 417.6)	0.4215
10	27.56654	25	0.3282	1.108330	(25, 417.6)	0.3286
11	16.39986	25	0.9024	0.650770	(25, 417.6)	0.9025
12	22.21640	25	0.6232	0.887619	(25, 417.6)	0.6235

Null hypothesis: No serial correlation at lags 1 to h

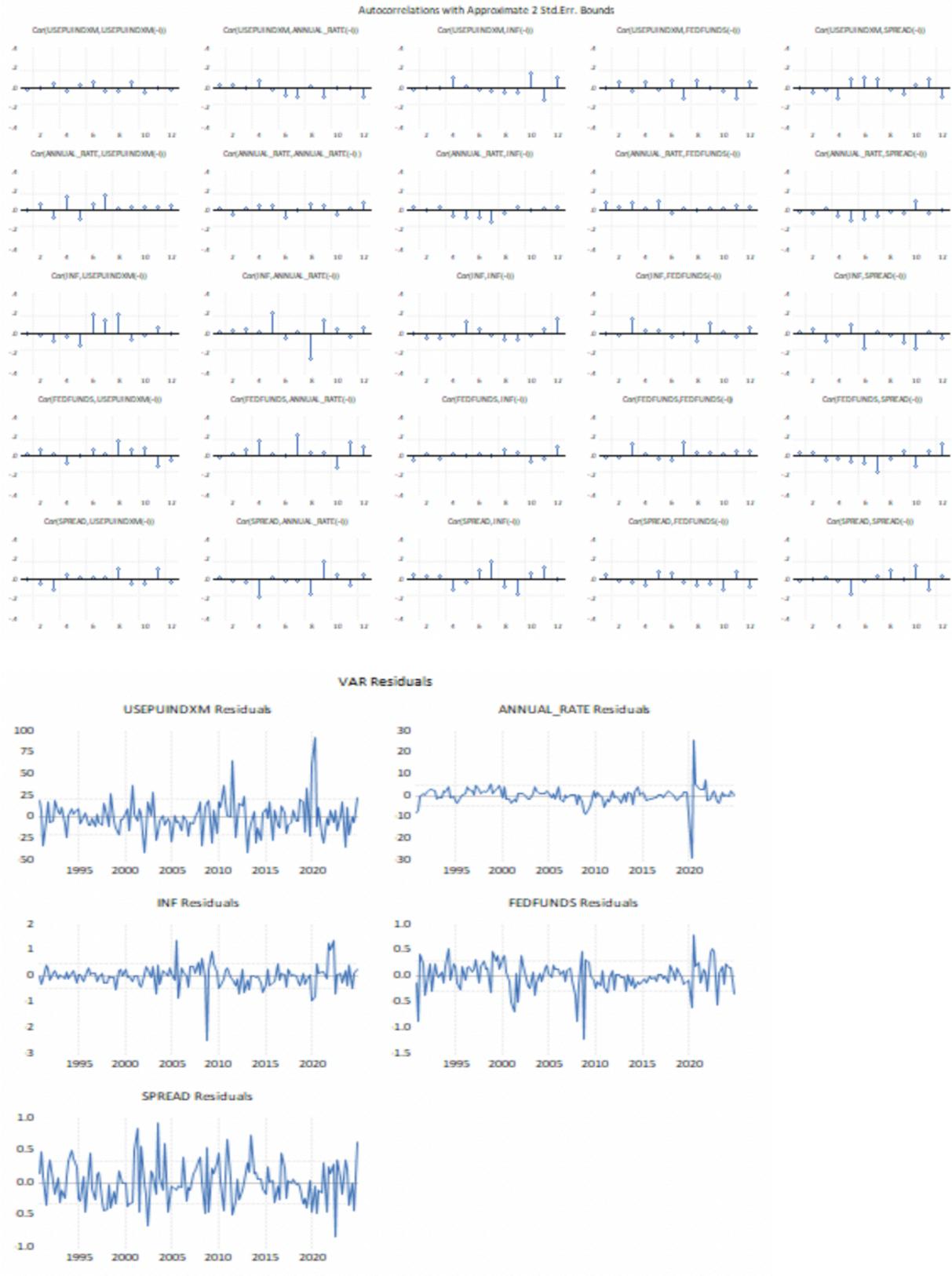
Lag	LRE* stat	df	Prob.	Rao F-stat	df	Prob.
1	21.80702	25	0.6469	0.870844	(25, 417.6)	0.6472
2	47.99898	50	0.5540	0.959251	(50, 491.4)	0.5555
3	83.17518	75	0.2424	1.118075	(75, 492.8)	0.2458
4	108.8568	100	0.2561	1.096728	(100, 477.9)	0.2634
5	142.6755	125	0.1333	1.158038	(125, 457.7)	0.1427
6	176.8238	150	0.0664	1.204577	(150, 435.3)	0.0762
7	207.7743	175	0.0457	1.217398	(175, 411.9)	0.0574
8	235.8005	200	0.0422	1.208349	(200, 387.9)	0.0590
9	267.0572	225	0.0286	1.219055	(225, 363.6)	0.0474
10	285.0841	250	0.0629	1.153981	(250, 339.1)	0.1105
11	306.4413	275	0.0933	1.112567	(275, 314.5)	0.1797
12	327.8746	300	0.1289	1.073313	(300, 289.8)	0.2723

*Edgeworth expansion corrected likelihood ratio statistic.

VAR Residual Heteroskedasticity Tests (n=137)
 Date: 04/30/25 Time: 11:14
 Sample: 1990Q1 2024Q4
 Included observations: 137

Joint test:

Chi-sq	df	Prob.
749.3211	450	0.0000



Dependent Variable: RECESSION_12M_AHEAD
 Method: ML - Binary Probit (Newton-Raphson / Marquardt steps)
 Date: 04/29/25 Time: 20:58
 Sample: 1990M01 2025M02 IF REGIME=1
 Included observations: 204
 Convergence achieved after 4 iterations
 Coefficient covariance computed using observed Hessian

Variable	Coefficient	Std. Error	z-Statistic	Prob.
SPREAD	0.377787	0.084045	4.495061	0.0000
C	-1.264050	0.191124	-6.613766	0.0000
McFadden R-squared	0.094859	Mean dependent var	0.284314	
S.D. dependent var	0.452197	S.E. of regression	0.429447	
Akaike info criterion	1.100312	Sum squared resid	37.25374	
Schwarz criterion	1.132843	Log likelihood	-110.2319	
Hannan-Quinn criter.	1.113472	Deviance	220.4637	
Restr. deviance	243.5684	Restr. log likelihood	-121.7842	
LR statistic	23.10472	Avg. log likelihood	-0.540352	
Prob(LR statistic)	0.000002			
Obs with Dep=0	146	Total obs		204
Obs with Dep=1	58			

Dependent Variable: RECESSION_12M_AHEAD
 Method: ML - Binary Probit (Newton-Raphson / Marquardt steps)
 Date: 04/29/25 Time: 21:00
 Sample: 1990M01 2025M02 IF REGIME=0
 Included observations: 207
 Convergence achieved after 8 iterations
 Coefficient covariance computed using observed Hessian

Variable	Coefficient	Std. Error	z-Statistic	Prob.
SPREAD	0.554890	0.150404	3.689318	0.0002
C	-2.468056	0.370045	-6.669611	0.0000
McFadden R-squared	0.147106	Mean dependent var	0.086957	
S.D. dependent var	0.282454	S.E. of regression	0.274530	
Akaike info criterion	0.523280	Sum squared resid	15.45019	
Schwarz criterion	0.555480	Log likelihood	-52.15949	
Hannan-Quinn criter.	0.536302	Deviance	104.3190	
Restr. deviance	122.3118	Restr. log likelihood	-61.15591	
LR statistic	17.99284	Avg. log likelihood	-0.251978	
Prob(LR statistic)	0.000022			
Obs with Dep=0	189	Total obs		207
Obs with Dep=1	18			

REFERENCES

- Smets, F., & Tsatsaronis, K. (1997). *Why does the yield curve predict economic activity?* BIS Working Paper No. 46.
- Bauer, M. D., & Mertens, T. M. (2018). *Economic Forecasts with the Yield Curve*. Federal Reserve Bank of San Francisco Economic Letter.
- Bloom, N. (2009). *The impact of uncertainty shocks*. *Econometrica*, 77(3), 623–685.
- Calvo, G. A. (1983). *Staggered prices in a utility-maximizing framework*. *Journal of Monetary Economics*, 12(3), 383–398.
- Christiano, L. J., Eichenbaum, M., & Evans, C. L. (1999). *Monetary policy shocks: What have we learned and to what end?* In *Handbook of Macroeconomics* (Vol. 1, pp. 65–148). Elsevier.
- Fuhrer, J. C., & Moore, G. R. (1995). *Inflation persistence*. *The Quarterly Journal of Economics*, 110(1), 127–159.
- Ludvigson, S. C., Ma, S., & Ng, S. (2021). *Uncertainty and business cycles: Exogenous impulse or endogenous response?* *American Economic Journal: Macroeconomics*, 13(4), 369–410.
- Svensson, L. E. O. (1996). *Inflation forecast targeting: Implementing and monitoring inflation targets*. NBER Working Paper No. 5797.
- Estrella, A., & Hardouvelis, G. A. (1991). *The Term Structure as a Predictor of Real Economic Activity*. *Journal of Finance*, 46(2), 555–576.
- Estrella, A., & Mishkin, F. S. (1996). *The Yield Curve as a Predictor of U.S. Recessions*. *Current Issues in Economics and Finance*, Federal Reserve Bank of New York.

Note on the Use of AI-based Tools

Language refinement and organizational suggestions in this thesis were supported using AI-based tools (specifically, OpenAI's ChatGPT). All analytical design, empirical work, and interpretations reflect the author's own reasoning, responsibility, and judgment.