Macroeconomic Analysis Investment Strategy

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Contents

1 Introduction

Macroeconomic conditions play a central role in shaping market behavior, investment performance, and policy responses. This project aims to conduct a data-driven macroeconomic analysis of the United States, assess its investment implications, and apply statistical and econometric techniques to interpret the evolution of economic cycles and financial-market dynamics. By integrating real economic indicators, financial-market data, and modern modeling approaches, the analysis provides an empirical foundation for understanding how shifts in growth and inflation influence asset performance across business-cycle regimes.

The study begins with a comprehensive examination of key U.S. macroeconomic trends from 2018 to 2025, identifying the prevailing economic environment and evaluating potential risks and opportunities. Ten major indicatorscapturing both growth and inflation dynamicsare selected to construct composite indices for real-time regime classification and nowcasting. This framework allows for an assessment of the current macroeconomic phase and its implications for cross-asset investment strategy.

Subsequent sections extend the analysis by exploring the leadlag structure of economic indicators, evaluating how leading and lagging signals align or diverge across different phases, including the COVID-19 recession. The report then examines conditional asset returns across business-cycle stages, revealing how sector performance, bond classes, and investment styles vary under Reflation, Deflation, Stagflation, and Recovery regimes. Finally, the project incorporates machinelearningbased nowcasting models for GDP, comparing their predictive performance to traditional autoregressive benchmarks to evaluate their usefulness in real-time economic monitoring.

Through this integrated approach, the report bridges macroeconomic theory with empirical analysis, offering quantitative insights into how data-driven methods can enhance understanding of economic cycles, improve forecasting accuracy, and inform investment decision-making in an evolving macro-financial landscape.

2 Data Source

The study relies on consistent, high-quality data sourced primarily from the Federal Reserve Economic Data (FRED) database maintained by the Federal Reserve Bank of St. Louis, and from the U.S. Bureau of Economic Analysis (BEA) for quarterly real GDP. This repository provides reliable, continuously updated time series for major U.S. macroeconomic variables covering January 2018 to the most recent available month in 2025, ensuring that the analysis captures both the COVID-19 recession and the subsequent recoverytwo of the most significant structural episodes in recent U.S. economic history.

Each indicator is carefully selected to represent either real-activity (growth) or price-level (inflation) dimensions of the economy. Growth indicators such as real GDP, industrial production, and the yield-curve slope provide insight into output momentum and forward expectations, while inflation indicators like CPI, core CPI, and credit spreads measure both realized and expected price pressures. For the leadlag analysis, additional data such as the Purchasing Managers Index (PMI) are obtained from Trading Economics, while the zero-coupon yield curve and other financial indicators are from FRED.

All macroeconomic series are harmonized to a monthly frequency for comparability and aggregation into composite indices. For the asset-return analysis, daily closing price data are collected from Yahoo Finance across 11 GICS sector ETFs, fixed-income instruments (HYG, LQD, IEF), investment styles (IVE, IVW), market caps (IWM, SPY), global exposures (EEM, EFA), and commodities and currencies (GLD, FXE, UUP). These datasets together enable a unified, data-driven evaluation of macroeconomic conditions, financial-market behavior, and investment performance across business-cycle regimes.

3 Macroeconomic Analysis and Investment Outlook

3.1 Macroeconomic Indicators Overview

This section introduces ten key macroeconomic indicators in the US, that will serve as the empirical foundation of the regime-based analysis introduced by Dr. Darius Dale. Each indicator captures a unique dimension of the U.S. economy-ranging from real growth momentum to inflationary pressure-and together they form the basis for classifying the prevailing macroeconomic regime (Reflation, Goldilocks, Stagflation, or Deflation). The indicators are selected based on their data availability, frequency, and historical significance in anticipating business-cycle turning points.

3.2 10 Indicators Definitions and Roles

This study employs ten key macroeconomic indicators, which we will categorize each into the *growth* and *inflation* dimensions of the economy. Each indicator is selected for its theoretical relevance, data availability, and empirical effectiveness in tracking business-cycle dynamics. Together, these measures provide a comprehensive foundation for constructing the Growth Index (GI) and Inflation Index (II) used in the nowcasting framework.

3.2.1 Growth Indicators

1. **Real GDP Growth (Quarterly % change)**
   Represents the inflation-adjusted change in the aggregate value of goods and services produced within the economy. Real GDP growth serves as the broadest measure of economic activity and defines the long-term trend of the business cycle. Sustained positive growth implies expansion, while negative growth indicates contractionary conditions.

2. **Industrial Production (Monthly % change)**
   Captures the physical output of factories, utilities, and mines. As a coincident indicator of manufacturing and energy activity, industrial production is highly sensitive to cyclical demand and thus reflects turning points in real economic momentum.

3. **Retail Sales (Monthly % change)**
   Measures household spending on goods and services, adjusted for seasonal variation. Since consumption constitutes roughly two-thirds of U.S. GDP, retail sales provide an early read on aggregate demand strength and consumer confidence.

4. **Unemployment Rate (Monthly % change)**
   Reflects labor-market slack and serves as a key inverse indicator of growth. A declining unemployment rate signals economic expansion and tighter capacity utilization, while an increase points to weakening output and labor demand.

5. **Yield Curve Slope (10-year minus 2-year Treasury spread)**
   A forward-looking financial indicator that captures market expectations for future growth and monetary policy. A steep yield curve (positive slope) suggests optimism and rising growth expectations, whereas an inversion (negative slope) historically precedes recessions.

3.2.2 Inflation Indicators

1. **Headline Consumer Price Index (CPI) (Monthly % change)**
   Measures the overall change in prices of a representative basket of goods and services. Headline CPI reflects the actual inflation experienced by consumers and incorporates volatile components such as food and energy.

2. **Core Consumer Price Index (Core CPI) (Monthly % change)**
   Excludes food and energy prices to isolate underlying inflation trends. Core CPI provides a more stable gauge of persistent price pressures and is closely monitored by policymakers, including the Federal Reserve.

3. **Inflation Expectations (Market-implied, 5-year rate)**
   Derived from Treasury Inflation-Protected Securities (TIPS) and nominal Treasury yields, this measure reflects the markets expectation of average inflation over the medium term. It captures forward-looking sentiment and complements observed inflation data.

4. **Real Yield (10-year TIPS yield % change)**
   Represents the inflation-adjusted return on long-term government bonds. Higher real yields indicate tighter financial conditions and lower expected future inflation, while declining real yields reflect easing conditions and inflationary bias.

5. **Credit Spreads (Moodys Baa corporate bond yield minus 10-year Treasury yield, basis points spread)**
   Measure the risk premium investors demand for holding corporate debt relative to risk-free Treasuries. Widening spreads suggest tightening credit conditions and rising recession risk, while narrowing spreads imply greater confidence and financial easing.

3.3 Visualization of Growth & Inflation Trends

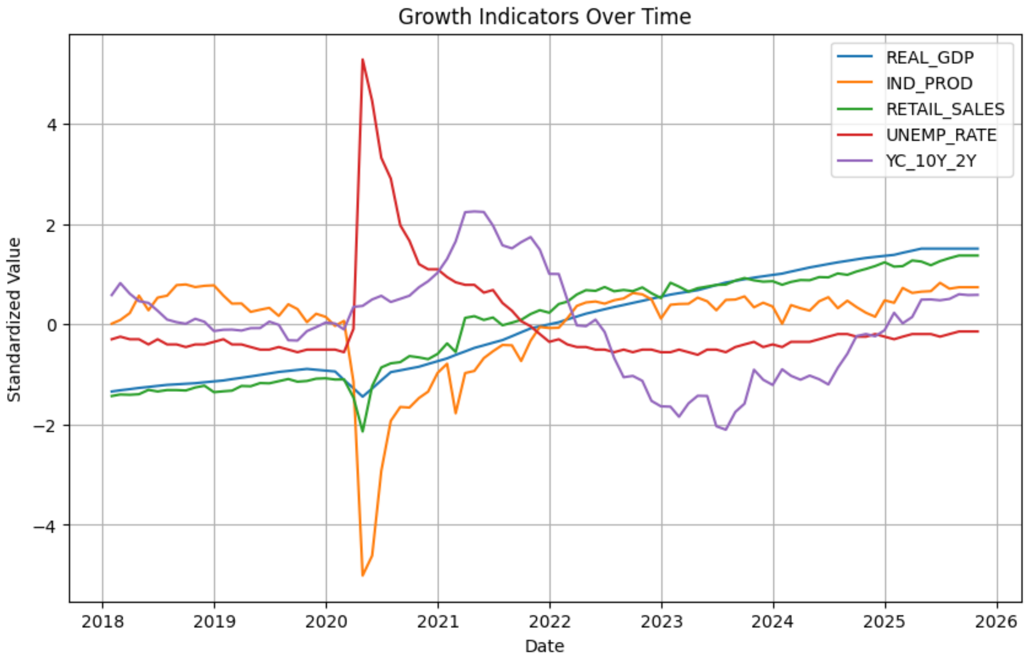


Figure 1: Growth Indicator from 2018 to 2025

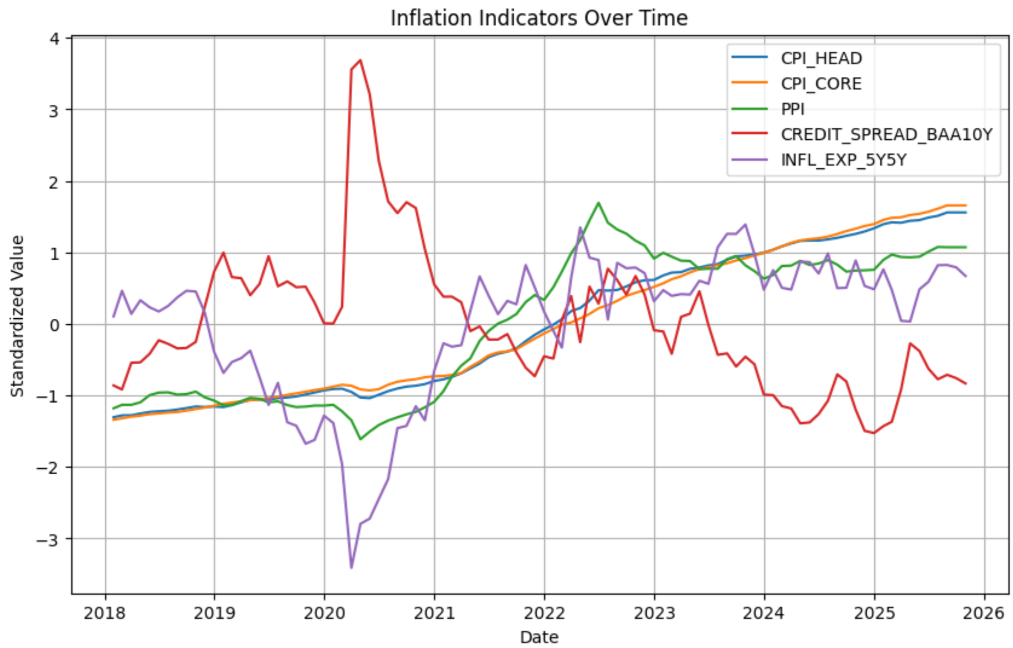


Figure 2: Inflation Indicator from 2018 to 2025

Figure 1 illustrates the standardized evolution of the five growth-related indicators from 2018 to 2025. The data reveal a sharp contraction across all real-activity measures during 2020, led by collapses in industrial production and retail sales, consistent with the pandemic-driven recession. The unemployment rate spiked simultaneously, while the yield curve steepened as policy rates were cut aggressively. From 2021 onward, all real indicators rebounded strongly, with real GDP and retail sales maintaining positive momentum through 2024 to 2025, signaling durable post-shock recovery and stable expansion. Meanwhile, the yield curve (10Y2Y spread) flattened and inverted around 2023, reflecting tightening financial conditions and forward expectations of policy normalization. Overall, the growth panel shows that while short-term volatility was high around 20202022, real activity has stabilized into a moderate, steady-growth regime thereafter.

Figure 2 tracks the inflation-related series over the same period. Both headline and core CPI, along with producer prices (PPI), surged following the 2021 reopening phase, marking the onset of the inflationary upcycle that peaked in 2022. Credit spreads narrowed as financial conditions normalized, while long-term inflation expectations remained broadly anchored after 2023, suggesting policy credibility in containing price pressures. By 2024 to 2025, headline and core inflation measures converged near trend levels, and producer prices moderated, confirming the disinflation process. Taken together, the inflation indicators point to a clear transition from overheating toward stability, supporting the interpretation of a soft-landing environment with reduced macro volatility and improving policy visibility.

3.4 Indicator Integration

Each five growth indicators from two aspects collectively describes the economys real output and momentum, while the five inflation indicators capture both realized and expected price dynamics. By standardizing each series into Z-scores and aggregating within their respective groups, we construct two composite indices:

$$GI_t = \frac{1}{N_g} \sum_{i=1}^{N_g} Z_{i,t}^{(\text{growth})}, \qquad II_t = \frac{1}{N_i} \sum_{j=1}^{N_i} Z_{j,t}^{(\text{inflation})}.$$

These indices jointly determine the U.S. economys current position within the four-quadrant macro regime framework developed in the following section.

3.5 Methodology: Constructing the Nowcasting Framework

3.5.1 Overview

Inspired by Darius Dale with his guest lecture, we seek to implement his macroeconomic analysis approach, which categorizes the macroeconomic environment into four canonical regimes based on the joint behavior of growth and inflation. The framework provides a practical lens for interpreting how shifts in macroeconomic momentum and price dynamics influence asset-class performance and portfolio positioning.

Specifically, the model distinguishes four distinct regimes:

- **Reflation:** Growth accelerating while inflation is rising. Characterized by strong demand and policy normalization, typically favoring equities and commodities.
- **Goldilocks:** Growth accelerating while inflation is falling. A favorable environment for risk assets, as economic activity expands without overheating price pressures.
- **Stagflation:** Growth decelerating while inflation is rising. Reflects cost-push inflation amid weakening demandoften challenging for both equities and fixed income.
- **Deflation:** Growth and inflation both decelerating. Represents broad economic slowdown and falling price levels, favoring high-quality bonds and defensive assets.

This framework forms the conceptual foundation of the nowcasting model constructed in this report, allowing for a data-driven classification of the U.S. economys current position within the business cycle.

3.5.2 Data Alignment and Frequency Adjustment

Macroeconomic indicators differ in reporting frequency (daily, monthly, or quarterly). To ensure consistency, all series $X_{i,t}$ are converted to a common monthly frequency. Daily or weekly data are averaged within each month, while quarterly data are forward-filled to cover all months within the quarter:

$$\tilde{X}_{i,t} = \begin{cases} \text{mean}(X_{i,d}), & \text{for daily/weekly data,} \\ X_{i,t}, & \text{for monthly data,} \\ \tilde{X}_{i,t} = X_{i,q} + \frac{t-T_q}{T_{q+1}-T_q}\big(X_{i,q+1} - X_{i,q}\big), & \text{Linear Interpolation for quarterly data} \end{cases}$$

where T_q and T_{q+1} denote the starting months of quarters q and $q+1$, respectively.

3.5.3 Indicator Standardization

Each indicator is standardized into a Z-score to remove unit and scale differences:

$$Z_{i,t} = \frac{\tilde{X}_{i,t} - \mu_i}{\sigma_i},$$

where μ_i and σ_i are the historical mean and standard deviation of indicator i. This transformation ensures comparability across indicators:

$$Z_{i,t} > 0 \Rightarrow \text{above-trend (expansionary/inflationary)}$$

$$Z_{i,t} < 0 \Rightarrow \text{below-trend (contractionary/disinflationary).}$$

3.6 Composite Index Construction

Each indicator is assigned to either the *growth* or *inflation* category. The two composite indices are constructed as standardized aggregates that summarize real economic momentum and inflationary pressure.

To mitigate redundancy and ensure statistical independence across inputs, one indicator from each category (Retail Sales for Growth category and Core CPI for inflation) that exhibits the highest pairwise correlation with the others is excluded from the composite calculation. This adjustment minimizes the risk of multicollinearity, which could otherwise overweight closely related variables and distort the composite index. The exclusion is determined based on the correlation matrix among standardized indicators (Z-scores), thereby retaining the most informationally diverse subset of metrics for both the growth and inflation components.

After refinement, the composite indices are computed as equal-weighted averages of the remaining standardized indicators:

$$GI_t = \frac{1}{N_g}\sum_{i=1}^{N_g} Z_{i,t}^{(\text{growth})}, \qquad II_t = \frac{1}{N_i}\sum_{j=1}^{N_i} Z_{j,t}^{(\text{inflation})},$$

where N_g and N_i denote the number of growth and inflation indicators retained after correlation screening, respectively.

3.7 Results and Interpretation

3.7.1 Composite Indices and Regime Dynamics

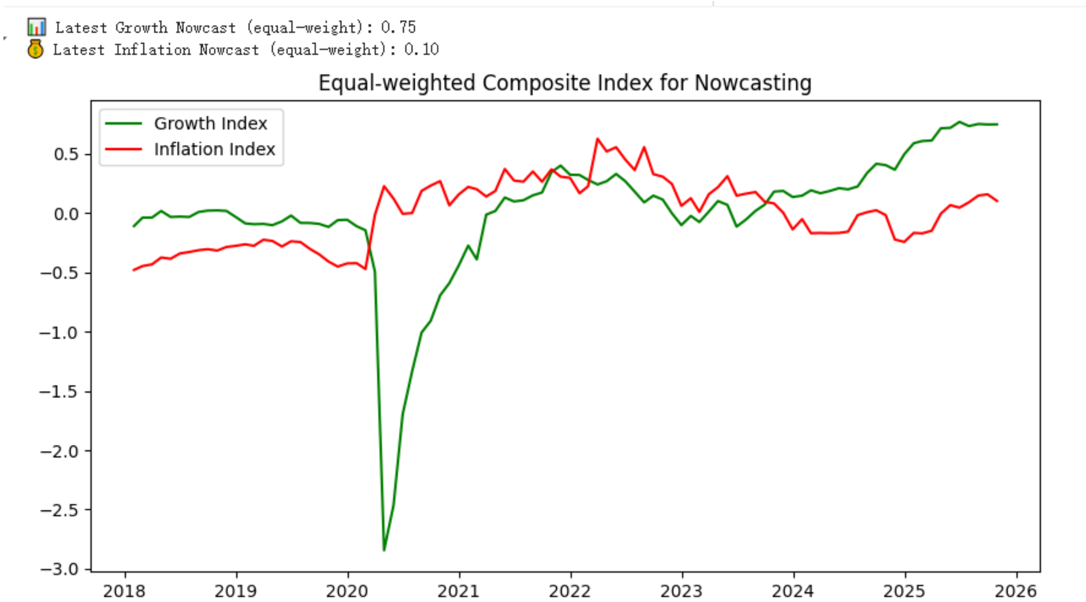


Figure 3: Equal-weighted composite indices for growth and inflation, 20182025. Shaded regions denote major macroeconomic phases. Source: Authors computation using FRED, BLS, and Treasury data.

Figure 3 presents the equal-weighted composite indices for growth and inflation from 2018 to 2025. The *Growth Index (GI)* (green) tracks real economic momentum, while the *Inflation Index (II)* (red) reflects price-level pressures. Both series are standardized, allowing for a direct comparison of macroeconomic cycles through time.

The results exhibit distinct macroeconomic phases consistent with known U.S. business-cycle developments:

- **2018 to Early 2020 (Weak Goldilocks/Reflation):** Growth Surround 0 and subdued inflation characterized the late-cycle expansion before the COVID-19 shock.
- **2020 (Deflation / Pandemic Recession):** A collapse in the Growth Index coincides with a brief inflation dip, reflecting an unprecedented contraction in output.
- **2021 to Mid 2022 (Reflation):** Rapid rebounds in both indices mark the reopening phase, fiscal stimulus, and strong demand recovery.
- **Late 2022 to 2023 (Stagflation):** Growth momentum fades while inflation remains elevated amid supply-chain stress and policy tightening.
- **2024 to 2025 (Recovery and Potential Goldilocks/Soft Landing):** An increased growth and moderated inflation, consistent with a soft-landing scenario and normalization of policy.

As of the most recent data, the Growth Index records a value of approximately 0.75, and the Inflation Index stands near 0.10. This positioning corresponds to a regime at the boundary between *Reflation* and *Goldilocks*, implying sustained expansion with contained inflationary pressure.

3.7.2 Three Most Contributing Indicators in Our Model

Among the ten macroeconomic indicators included in this study, three stand out as particularly influential in shaping regime classification outcomes: the *Yield Curve Spread (10Y2Y)*, *Industrial Production*, and the *Producer Price Index (PPI)*. Each captures a distinct macroeconomic dimensionfinancial expectations, real activity, and cost dynamicsmaking them central to interpreting regime transitions.

Yield Curve Spread (10Y2Y). The yield curve measures the difference between long- and short-term Treasury yields and serves as a forward-looking gauge of market expectations for growth and monetary policy. A steepening curve typically signals reflationary conditions driven by policy easing and improving demand, whereas an inversion often precedes economic slowdowns or recessions. Within the nowcasting framework, the yield curve acts as an early-warning signal of regime shifts, especially transitions from *Reflation* to *Stagflation* or *Deflation*. However, it should be noted that inversions can persist for extended periods before real activity turns downward, implying that the signal should be interpreted probabilistically rather than deterministically.

Industrial Production. Industrial production captures the physical output of manufacturing, mining, and utilities, making it a high-frequency proxy for real economic momentum. Its sharp decline in 2020 and subsequent rebound illustrate its sensitivity to cyclical turning points, aligning closely with both the troughs and recoveries of the business cycle. Because it reacts quickly to shifts in aggregate demand and supply chain disruptions, industrial production provides a clear measure of the economys current trajectory. Nevertheless, its volatility can occasionally exaggerate short-term fluctuations, and revisions to historical data may alter the apparent timing of inflection points.

Producer Price Index (PPI). The PPI measures price changes at the wholesale level and serves as a leading indicator of inflationary trends. It typically peaks ahead of consumer price measures such as CPI, reflecting cost pressures passed along production chains. In this analysis, the sharp increase in PPI during 20212022 followed by a rapid normalization in 2023 was a defining signal of the transition from a *Stagflation* regime toward *Recovery*. However, because producer prices are sensitive to global commodity shocks and supply bottlenecks, the indicator can temporarily overstate underlying inflation momentum. Hence, PPI movements are best interpreted in conjunction with core CPI and inflation-expectation measures to distinguish cyclical from transitory cost effects.

3.7.3 Month-to-Month Changes and Macroeconomic Risk

To assess volatility and transition risk, Figure 4 plots the month-to-month changes in both indices, defined as:

$$\Delta GI_t = GI_t - GI_{t-1}, \qquad \Delta II_t = II_t - II_{t-1}.$$

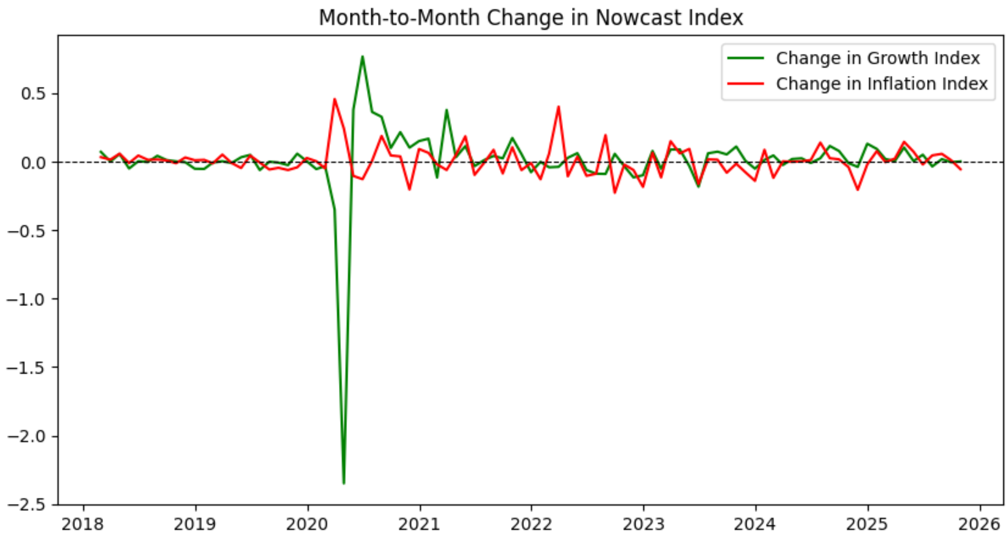


Figure 4: Month-to-month change in the Growth and Inflation Indices, 20182025. The amplitude of movements captures macroeconomic volatility and regime-transition risk.

The month-to-month changes in the Growth and Inflation Indices also provide valuable information about the economys underlying volatility and transition dynamics. Following the high amplitude fluctuations observed during 2020 to 2022, both ΔGI_t and ΔII_t exhibit a pronounced decline in volatility beginning in 2023. This contraction in macroeconomic variance implies that systemic uncertainty has fallen, reflecting the normalization of both real activity and price dynamics.

Formally, lower conditional variances of the month-to-month changes,

$$\sigma^2_{\Delta GI,t} = \mathrm{Var}(\Delta GI_{t-h:t}), \qquad \sigma^2_{\Delta II,t} = \mathrm{Var}(\Delta II_{t-h:t}),$$

indicate greater macro stability and reduced risk of abrupt regime shifts. This stabilization period represents a natural transition from the preceding *Stagflation* regime toward an intermediate *Recovery* phase, rather than an instantaneous move to a Goldilocks environment. As volatility in both growth and inflation continues to subside through 2024 to 2025, the model believes a high chance in a soft landing scenario characterized by moderate growth, a stabilizing inflation, and low macroeconomic risk conditions consistent with the early stage of a *Goldilocks* regime.

3.7.4 Macroeconomic Risk (Volatility of Monthly Changes) and Strategy

To quantify the volatility level above, we implement the month-to-month changes in the composite indices by

$$\Delta GI_t = GI_t - GI_{t-1}, \qquad \Delta II_t = II_t - II_{t-1}.$$

For each calendar year y, let $\mathcal{T}(y)$ be the set of months in year y with size n_y. We compute the *annual* standard deviations of the monthly changes as

$$\sigma_{\Delta GI}(y) = \sqrt{\frac{1}{n_y - 1} \sum_{t \in \mathcal{T}(y)} \left(\Delta GI_t - \overline{\Delta GI}_y\right)^2}, \qquad \sigma_{\Delta II}(y) = \sqrt{\frac{1}{n_y - 1} \sum_{t \in \mathcal{T}(y)} \left(\Delta II_t - \overline{\Delta II}_y\right)^2},$$

where $\overline{\Delta GI}_y$ and $\overline{\Delta II}_y$ are the within-year means of ΔGI_t and ΔII_t, respectively.

The *Macroeconomic Risk Index* for year y is then defined as the *sum of volatilities*:

$$\boxed{MRI(y) \; = \; \sigma_{\Delta GI}(y) \; + \; \sigma_{\Delta II}(y)}.$$

Using the sum (rather than an average) improves dispersion and makes cross-year differences more distinguishable.

3.8 Empirical Pattern and Interpretation

📊 Macro Risk Table (Annual Volatility of Month-to-Month Changes)

DATE	σ(△GI)	σ(△II)	MRI (sum)	Risk Level
2018	0.04	0.02	0.06	🟢 Low
2019	0.04	0.04	0.08	🟢 Low
2020	0.78	0.18	0.96	🔴 High
2021	0.13	0.09	0.22	🟡 Moderate
2022	0.06	0.17	0.23	🟡 Moderate
2023	0.09	0.10	0.18	🟡 Moderate
2024	0.05	0.09	0.14	🟡 Moderate
2025	0.04	0.06	0.10	🟡 Moderate

Figure 5: Month-to-month change in the Growth and Inflation Indices, 20182025. The amplitude of movements captures macroeconomic volatility and regime-transition risk.

Table 5 reports $\sigma_{\Delta GI}(y)$, $\sigma_{\Delta II}(y)$, and $MRI(y)$ for 2018 to 2025.[1] The results display a clear regime narrative:

1. **2018–2019 (Low MRI):** Small, stable monthly changes in both indices $\Rightarrow$ low macro uncertainty consistent with a late-cycle Goldilocks expansion.
2. **2020 (High MRI spike):** A sharp jump in $\sigma_{\Delta GI}$ and a concurrent rise in $\sigma_{\Delta II}$ capture the pandemic shock and policy whipsaw $\Rightarrow$ systemic macro risk.
3. **2021–2023 (Moderate MRI):** Volatility normalizes from crisis levels but remains elevated as growth re-accelerates and inflation dynamics are unstable (reopening, supply shocks, tightening).
4. **2024–2025 (Moderate trending lower):** Continued decline in both $\sigma_{\Delta GI}$ and $\sigma_{\Delta II}$ indicates stabilization of real activity and inflation $\Rightarrow$ soft-landing recovery and potentially moving toward early Goldilocks.

For a simple classification, define risk tiers using empirical percentiles of $MRI(y)$ over the sample:

$$MRI(y) \geq 0.5 \Rightarrow \text{High risk}, \quad MRI(y) \leq 0.5 \Rightarrow \text{Low risk}, \quad \text{else Moderate}.$$

Under this rule, 2020 is flagged *High*, 2018–2019 *Low*, and 2021–2025 *Moderate* with a downward trend into 2025.

3.8.1 Risk–Aligned Asset Guidance looking into 2026

With $MRI(2025)$ in the *moderate-but-declining* range and the level indices showing $GI > 0$ and $II \approx 0$, the outlook is approaching a soft-landing recovery transitioning toward early Goldilocks. This supports a **Buy/Hold** stance tilted to quality growth equities, investment-grade credit, and moderate duration, while keeping commodities and energy underweight and maintaining light defensive hedges for policy or growth surprises while the inflation risk is still relatively high.

[1] Computed from the month-to-month changes shown in Figure 4.

4 Lead/Lag Analysis of Economic Indicators

4.1 Introduction

Economics is often described as moving in a cyclical, sometimes messy, pattern. During a recession, consumers tend to tighten their wallets while companies build up inventories in anticipation of improving conditions. Asset valuations may fall, and businesses are cautious in their investments. Eventually, for various reasons, families start to spend a bit more, businesses need to replenish inventories, and production ramps up. As these changes snowball, economic recovery and expansion follow.

However, this cycle is rarely precise. It is extremely difficult to definitively pinpoint when a recession, recovery, or expansion begins. By tracking leading indicators, we can try to anticipate the upcoming stages of the cycle, while lagging indicators confirm trends that have already emerged. In this section, we explore these indicators, analyze the patterns of past economic cycles, and look at how leading and lagging indicators help forecast and confirm shifts in the economy.

4.2 Definition of Leading and Lagging Indicators

4.2.1 Leading Indicators

Leading indicators help predict future economic activity, signaling the direction in which the economy is heading. They precede significant economic events, offering a forecast of whats to come. Below are key leading indicators often used in economic analysis:

- **PMI (Purchasing Managers' Index)**: PMI measures the economic health of the manufacturing sector. It surveys purchasing managers about their outlook for the economy, covering areas like new orders, production, and employment. A PMI value above 50 indicates expansion, while below 50 signals contraction.

- **Interest Rate Spread**: The difference between long-term and short-term interest rates is a key indicator of future economic conditions. A positive spread suggests economic expansion, while a negative spread (an inverted yield curve) often predicts a recession.

- **Zero Curve for One-Year Coupon**: This is a model of the yield curve that represents the interest rate at each term to maturity for zero-coupon bonds, reflecting the long-term economic outlook.

4.2.2 Lagging Indicators

Lagging indicators provide confirmation of past economic events. They show the outcomes of changes in the economy and are used to validate the trends shown by leading indicators.

- **Unemployment Duration**: The average duration of unemployment is a key lagging indicator, confirming economic recovery or downturn based on the length of time individuals are out of work.

- **Commercial and Industrial Loans**: The amount of loans given to commercial and industrial businesses reflects the strength of business investment, which typically lags the overall economic cycle.

- **CPI for Services**: The Consumer Price Index (CPI) for services measures the price changes for services over time. An increase in CPI for services indicates inflationary pressures, providing a reflection of past economic conditions.

4.3 Methods

To analyze the economic cycle and evaluate the behavior of leading and lagging indicators, the following steps were taken:

4.3.1 Data Collection

Six economic indicators were collected for the period from January 1, 2019, to September 30, 2025, chosen for their ability to capture both leading and lagging economic trends.

Leading indicators include the Purchasing Managers' Index (PMI) from Trading Economics, the interest rate spread from FRED, and the zero curve for one-year coupon bonds, also from FRED. These indicators help predict future economic trends.

lagging indicators include the average duration of unemployment, commercial and industrial loans, and the Consumer Price Index (CPI) for services, all sourced from FRED.

These indicators confirm past economic trends and reflect the economy's historical performance.

4.3.2 Data Transformation

For certain indicators like interest rate spread and zero curve data, which were originally recorded on a daily basis, I transformed these to monthly data by averaging by month.

4.3.3 Combination of Indicators

Each indicator was standardized to avoid variation within indicators by converting each value into a unitless score, where each indicator had a mean of zero and a standard deviation of one. This step was crucial as it eliminated the influence of differing scales and allowed the indicators to be weighted accordingly. Once standardized, the leading and lagging indicators were combined into two composite indices using equally weighted summation. This approach provided a more holistic view of economic conditions, with one composite index representing the Leading Indicator and the second representing the lagging Indicator.

4.3.4 Smoothing

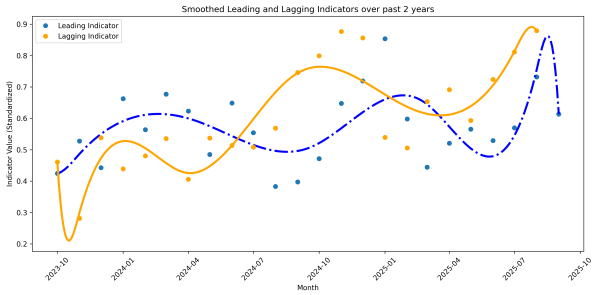
To reduce noise and better visualize the trends in the data, I applied the B-splines method to interpolate and smooth the curves of both leading and lagging indicators. This method helped create continuous curves that made it easier to see broader trends and cyclical patterns over time.

4.3.5 Time Frames for Comparison

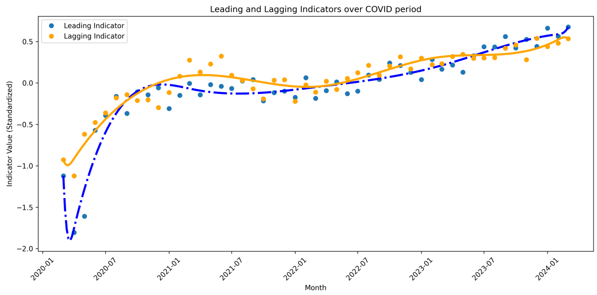
The analysis was broken down into two key time frames:

- **The past two years**: This allowed for a recent, high-resolution view of economic cycles.
- **The COVID period (2020-2022)**: This period was selected for comparison due to the unique economic disruptions caused by the pandemic, making it an important phase to understand how the indicators behave during such an unprecedented event.

4.4 Results



(a) Trend over past 2 years



(b) Trend over COVID period

The graph in Figure (a) illustrates the behavior of leading and lagging indicators over the past two years, which corresponds to a normal business cycle. As expected in typical economic conditions, the leading indicator, represented by the blue line, rises first, signaling a forthcoming economic expansion. Following a few months of delay, the lagging indicator, represented by the orange line, follows the trend, confirming the initial positive movement. This pattern is consistent with the well-established business cycle dynamics, where leading indicators anticipate economic shifts, and lagging indicators reflect the outcomes of such shifts after a certain period.

Over the past two years, the timing of turning points suggests a clear leadlag relationship of roughly six to eight months. Reading the smoothed curves, the leading indicator reaches local peaks firstaround January to March 2024and then again in January to February 2025. The lagging indicator follows much later, peaking about September to November 2024 and again in August to September 2025. That staggered pattern implies a lead of around seven to eight months at the top of the cycle. The troughs tell the same story. The leading indicator bottoms out in roughly August to September 2024, whereas the lagging indicator does not trough until about April to May 2025, again implying a gap of approximately seven to eight months. Taken together, these dates indicate that the leading series typically turns six to eight months before broader economic conditionsas proxied by the lagging seriesadjust. Put differently, the lagging indicator systematically trails the leading measure by six to eight months. The consistency across both peaks and troughs reinforces the impression that this leadlag structure is not a one-off quirk but a persistent feature of the data over the period examined.

In contrast, Figure (b) displays the trend of the same indicators during the COVID-19 period, which saw significant economic stagnation. In this period, the leading and lagging indicators exhibit minimal variation, indicating a much more synchronized movement. The absence of the usual lag between the indicators suggests that the extraordinary nature of the pandemic may have led to a convergence of these typically distinct signals. This alignment could be attributed to the unique and widespread disruptions in the economy, where traditional economic mechanisms were less predictable, leading to both indicators reacting more simultaneously in response to the same economic conditions.

4.5 Forecasting and Policymaking Based on Economic Stagnation

During the COVID period, the economy experienced stagnation, as evidenced by minimal movement in key indicators. This lack of variation suggests a halt in the typical business cycle. The simultaneous rise of both unemployment and inflation created a challenging environment for policymakers, making it difficult to navigate interest rate decisions, as any action could have negative consequences. This falls into "damn if you do, or damn if you don't."

In response to this uncertainty, both economic forecasters and policymakers are increasingly relying on scenario-based forecasting. Economic models now account for various potential scenarios, including stagnation, stagflation, and a "soft landing." The Federal Reserve, along with private-sector analysts, employs distributional forecasting to assess the likelihood of these scenarios, factoring in risks such as supply shocks and the effects of policy measures, including tariffs.

4.6 Conclusion

Our team explored how leading and lagging economic indicators provide insights into the state of the economy, especially in light of the ongoing stagnation risks. By analyzing the smoothing of these indicators and considering the complex interplay between economic stagnation and stagflation, it becomes clear that decision-makers must adopt a balanced approach in their policy choices. Effective forecasting and planning require timely data, coordination between monetary and fiscal policies, and scenario-based planning to prepare for a variety of potential economic outcomes for any possible situation.

5 Conditional Asset Returns by Business Cycle Phase

5.1 Defining the Business Cycle

In Section 3, the economic cycle we nowcast is divided into four phases based on growth and inflation dynamics: Reflation (accelerating growth with rising inflation, driven by strong demand and policy normalization, favoring equities and commodities); Goldilocks (accelerating growth with falling inflation, ideal for risk assets without overheating); Stagflation (decelerating growth amid rising inflation from cost-push pressures in weak demand, challenging for equities and fixed income); and Deflation (deceleration in both growth and inflation, signaling slowdowns and benefiting high-quality bonds and defensive assets). The framework employs a hybrid nowcasting model inspired by Darius Dale, similar to Ray Dalio's GRID but tailored to U.S. data from 2018 to 2025, using a four-quadrant grid for regime classification via composite indices from standardized macroeconomic indicators.

The methodology constructs the Growth Index (GI) and Inflation Index (II) from ten indicators (five each for growth and inflation), refined through correlation analysis to exclude redundancies like Retail Sales and Core CPI for statistical independence; phases are identified by the indices' signs and month-to-month changespositive in both for Reflation, positive GI with negative II for Goldilocks, negative GI with positive II for Stagflation, and negatives in both for Deflationjustified by empirical alignment with U.S. cycles, forward-looking nature, and real-time detection.

5.2 Return Analysis

This analysis computes average and median conditional returns for various asset classes across the cycle phasesReflation, Deflation, Stagflation, and Recoverydefined in Section 3 of the PDF, using data from January 2018 to October 17, 2025. Data was downloaded using yfinance for the specified tickers: XLK, XLF, XLE, XLV, XLY, XLP, XLI, XLC, XLRE, XLB, XLU (11 GICS sectors), HYG, LQD, IEF (Junk bonds, Investment Grade, Treasury bonds), IVE, IVW (Value and Growth Investing), IWM, SPY (Small Cap and Large Cap), EEM, EFA (Emerging and Developed Markets), and GLD, FXE, UUP (Gold, Foreign Currencies(EU), US Dollar). Those returns were aligned with defined phases based on the Section 3: Reflation (2018-01-01 to 2020-01-31 and 2021-01-01 to 2022-06-30), Deflation (2020-02-01 to 2020-12-31), Stagflation (2022-07-01 to 2023-12-31), and Recovery (2024-01-01 to 2025-10-17), replacing Goldilocks with Recovery due to the absence of a true Goldilocks regime. We then calculate the average and median conditional returns on these regimes, which are shown in the Table 1.

Table 1: Average and Median Conditional Returns by Cycle Phase (2018-2025, in %)

Ticker	Reflation		Deflation		Stagflation		Recovery	
	Avg	Med	Avg	Med	Avg	Med	Avg	Med
XLK	0.055	0.089	0.174	0.367	0.125	0.126	0.102	0.190
XLF	0.030	0.074	0.048	0.081	0.062	0.030	0.083	0.157
XLE	0.067	0.079	-0.041	-0.312	0.072	0.069	0.026	0.171
XLV	0.044	0.121	0.085	-0.014	0.027	0.023	0.020	0.033
XLY	0.020	0.141	0.137	0.212	0.085	0.119	0.071	0.128
XLP	0.034	0.057	0.057	0.080	0.013	0.066	0.033	0.052
XLI	0.018	0.092	0.080	0.185	0.084	0.149	0.075	0.061
XLC	-0.006	0.091	0.124	0.182	0.092	0.040	0.111	0.173
XLRE	0.050	0.127	0.019	0.054	0.019	0.000	0.028	0.063
XLB	0.009	0.035	0.139	0.221	0.057	0.104	0.020	0.040
XLU	0.060	0.103	0.006	0.051	-0.007	0.000	0.099	0.175
HYG	0.000	0.014	0.027	0.083	0.039	0.000	0.032	0.049
LQD	-0.004	0.035	0.041	0.066	0.020	-0.027	0.022	0.037
IEF	-0.002	0.000	0.027	0.029	-0.003	-0.032	0.018	0.032
IVE	0.031	0.083	0.044	0.059	0.075	0.061	0.047	0.057
IVW	0.033	0.092	0.140	0.323	0.070	0.028	0.114	0.149
IWM	0.001	0.080	0.128	0.251	0.062	0.045	0.058	0.071
SPY	0.033	0.073	0.097	0.271	0.073	0.038	0.084	0.110
EEM	-0.027	0.071	0.120	0.265	0.018	-0.050	0.079	0.127
EFA	-0.005	0.074	0.065	0.139	0.065	0.014	0.065	0.096
GLD	0.016	0.039	0.085	0.204	0.037	0.006	0.168	0.197
FXE	-0.029	-0.010	0.039	0.045	0.019	0.040	0.020	-0.010
UUP	0.030	0.038	-0.033	-0.040	0.012	0.034	0.016	0.036

The heatmap analysis of average and median conditional returns across the Reflation, Deflation, Stagflation, and Recovery phases from 2018 to 2025 reveals several key insights. First, it is notable that median returns are generally slightly higher than average returns across most tickers and phases, suggesting a positive skew in daily return distributions.

Second, the Deflation phase (2020-02-01 to 2020-12-31) exhibits significant volatility, with several tickers such as XLK (Technology), XLE (Energy), IVW (Growth Investing), IWM (Small Cap), SPY (Large Cap), EEM (Emerging Markets), and GLD (Gold) showing pronounced fluctuations. This period aligns with the 2020 Pandemic Recession, when

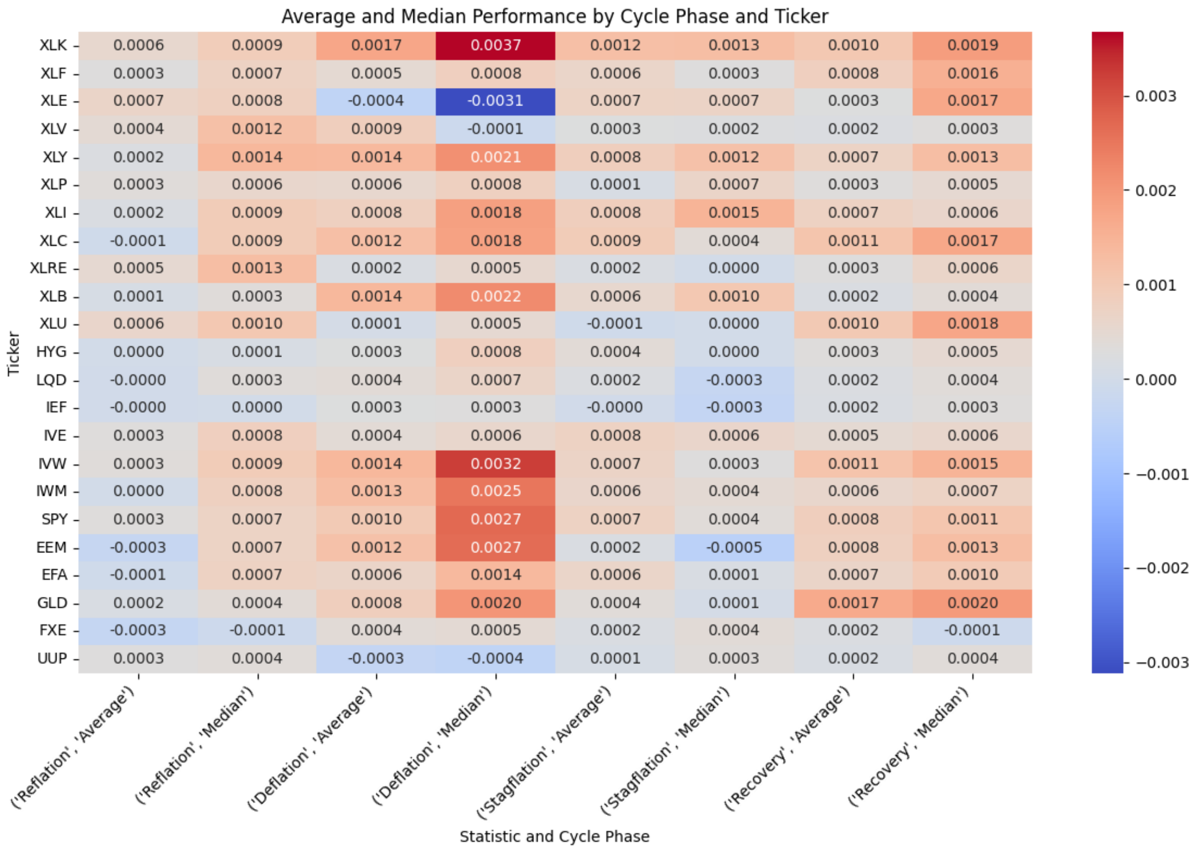


Figure 7: Heatmap of Average and Median Conditional Returns Across Cycle Phases

a collapse in the Growth Index coincided with an unprecedented contraction in output, likely amplifying risk and return variability. Specifically, XLK and IVW, representing growth-oriented technology and large-cap growth stocks, experienced sharp declines due to disrupted supply chains and reduced consumer spending, while EEM reflected emerging market vulnerabilities to global demand shocks. The significant decline in XLE's median return was driven by a collapse in oil demand and prices amid the 2020 pandemic lockdowns. Conversely, GLD saw increased demand as a safe-haven asset, and IWMs small-cap focus amplified its sensitivity to economic uncertainty, contributing to the observed volatility.

Third, certain tickers, including HYG (Junk bonds), LQD (investment-grade bonds), and IEF (Treasury bonds), demonstrate relatively stable returns with minimal variation across all phases, indicating resilience or lower sensitivity to macroeconomic regime shifts. This stability likely stems from their roles as safe-haven assets, with HYG offering higher yields despite credit risk, LQD providing a balanced exposure to investment-grade bonds, and IEF benefiting from the stability of intermediate-term U.S. Treasuries. These assets tend to perform consistently during economic instability, such as the Deflation and Stagflation phases, where their low correlation with equity markets helps buffer portfolio volatility, reinforcing their utility in diversified investment strategies.

Overall, the heatmap highlights how business cycle dynamics drive asset performance across the defined regimes. These insights provide a data-driven foundation for portfolio adjustments across economic cycles, enabling investors to capitalize on growth opportunities in Reflation and Recovery (e.g., technology and energy sectors like XLK and XLE) while maintaining stability with bonds like IEF and LQD during downturns. The observed volatility in Deflation underscores the need for dynamic asset allocation, particularly favoring defensive assets like GLD, while the consistent performance of HYG, LQD, and IEF suggests a strategic role for fixed-income securities in mitigating risk across all phases, aligning with the forward-looking approach advocated in Section 3 of the analysis.

6 Literature Review: Nowcasting GDP

6.1 Nowcasting growth using Google Trends data: A Bayesian approach

Kohns and Widmann (2023) proposed a Bayesian structural time-series (BSTS) framework for nowcasting real GDP growth using Google search activity as high-frequency predictors. Their approach expands the traditional local-level model by incorporating a large set of search-based and macroeconomic indicators, while employing Bayesian shrinkage priors to control for overfitting in a high-dimensional environment.

Formally, the BSTS model is expressed as:

$$y_t = \mu_t + \beta^\top z_t + \varepsilon_t, \qquad \mu_t = \mu_{t-1} + \nu_t,$$

where y_t denotes quarterly GDP growth, μ_t is a latent level component, z_t is a vector of predictors (e.g., Google search indices), and ε_t, ν_t are Gaussian disturbances. To prevent over-parameterization, the authors impose globallocal shrinkage priors on β, such as the horseshoe prior, allowing strong predictors to remain influential while shrinking irrelevant coefficients toward zero.

This framework allows real-time density nowcasts through Bayesian posterior simulation. Empirical evaluations on U.S. data show that incorporating Google Trends data improves early-quarter forecast accuracy and enhances the calibration of predictive intervals relative to benchmark models. The authors conclude that search-based information carries timely signals about consumer and business sentiment, particularly before official macroeconomic indicators are released. However, they note that stability can deteriorate during structural breaks, suggesting the need for time-varying parameter or regime-switching extensions.

6.2 Forecasting GDP growth rates in the United States and Brazil using Google Trends

Bantis, Clements, and Urquhart (2023) adopt a dynamic factor modeling (DFM) framework to nowcast GDP growth in the United States and Brazil, combining standard monthly indicators with Google Trends data. Their model addresses the mixed-frequency challenge between monthly predictors and quarterly GDP by constructing latent factors that capture common movements across multiple variables.

The DFM is formulated as:

$$x_t = \Lambda f_t + u_t, \qquad f_t = \Phi f_{t-1} + w_t, \qquad y_t = \gamma^\top f_t + \eta_t,$$

where x_t is a vector of high-frequency indicators, f_t are latent factors, and y_t denotes quarterly GDP. Estimation proceeds in two stages: principal component extraction for factor estimation and Kalman filtering to handle missing observations (ragged-edge data). Before factor estimation, the authors apply penalized regressions such as LASSO to preselect relevant Google categories, ensuring that noise from excessively granular search terms does not overwhelm the model.

Their results demonstrate that augmenting macroeconomic indicators with selected Google search variables improves early-quarter nowcasting accuracy in both economies. The benefit diminishes once traditional hard data, like industrial production or retail sales, are available. The authors conclude that Google Trends data provide timely supplementary information but should be used selectively and with appropriate dimension reduction. They also emphasize the importance of pseudoreal-time evaluation and consistent transformation of search indices to ensure replicability.

6.3 Nowcasting GDP using machine learning methods

Kant, Pick, and de Winter (2024) evaluate the predictive performance of traditional econometric and modern machine learning approaches in nowcasting quarterly GDP for the Netherlands. Using 83 monthly macroeconomic and financial indicators from 1992Q1 to 2018Q4, the authors conduct a comprehensive pseudoreal-time forecasting exercise to compare models such as the Dynamic Factor Model (DFM), Mixed-Data Sampling (MIDAS) regression, LASSO, Elastic Net, Random Subspace Regression, and Random Forests.

Their general framework can be expressed as:

$$\hat{y}_{t+h|t} = \mathcal{M}(X_t; \theta),$$

where $\hat{y}_{t+h|t}$ denotes the nowcast of GDP h periods ahead, X_t is the matrix of monthly predictors, and $\mathcal{M}(\cdot)$ represents the forecasting model parameterized by θ. Each model is re-estimated recursively using an expanding window to mimic real-time forecasting conditions, and predictive accuracy is assessed through the root mean square forecast error (RMSFE).

Empirical results show that the Random Forest model consistently outperforms the DFM, MIDAS, and regularization-based approaches in most forecasting and nowcasting horizons, particularly during and after the 2008 financial crisis. The DFM, however, remains superior for backcasting historical GDP values, while LASSO and Elastic Net perform robustly in volatile periods. To enhance interpretability, the authors employ Shapley values to identify the most influential predictors, revealing that survey-based and production indicators contribute significantly to nowcast accuracy.

To conclude, the study demonstrates that nonlinear ensemble methods can substantially improve short-term GDP nowcasting over traditional linear frameworks, while emphasizing the importance of interpretability and robustness in policy applications. These findings motivate the exploration of gradient boosting algorithms, such as LightGBM, to assess whether they can further enhance predictive performance beyond Random Forests.

Building on this literature, the following section implements a LightGBM-based nowcasting model and compares its predictive performance against a baseline AR(1) framework.

7 Machine Learning for GDP Nowcasting

7.1 Model motivation and framework

Building on the empirical framework of Kant et al. (2024), this study first implements a gradient boosting approach to nowcast quarterly GDP using monthly macroeconomic indicators. Gradient boosting models such as LightGBM extend the Random Forest framework by iteratively minimizing prediction errors and reweighting difficult-to-predict observations, which allows them to capture complex nonlinear relationships and variable interactions that are often missed by linear econometric models.

Formally, LightGBM constructs an additive ensemble of regression trees:

$$\hat{y}_t = \sum_{m=1}^{M} f_m(X_t), \qquad f_m \in \mathcal{F},$$

where each f_m represents a regression tree, and $\mathcal{F}$ denotes the space of all possible trees. The model minimizes the following objective:

$$\mathcal{L} = \sum_{t=1}^{T} \ell(y_t, \hat{y}_t) + \sum_{m=1}^{M} \Omega(f_m),$$

with loss function $\ell(\cdot)$ (e.g., squared error) and regularization term $\Omega(f_m)$ controlling tree complexity. This setup balances model flexibility and generalization, making it suitable for small to medium-sized macroeconomic datasets.

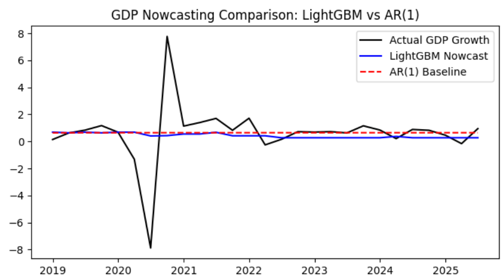
7.2 Experimental design and model comparison

Following a pseudoreal-time setup, quarterly GDP growth (y_t) serves as the target variable, while the predictor matrix (X_t) includes monthly indicators such as industrial production, retail sales, unemployment, inflation, and financial variables. Data are aligned using the most recent available monthly releases to approximate real-time information (ragged-edge adjustment). Model evaluation follows an expanding-window forecasting scheme, where both LightGBM and a baseline autoregressive model of order one [AR(1)] are re-estimated at each step to nowcast the current quarters GDP. Predictive accuracy is assessed using RMSE, MAE, and R^2.

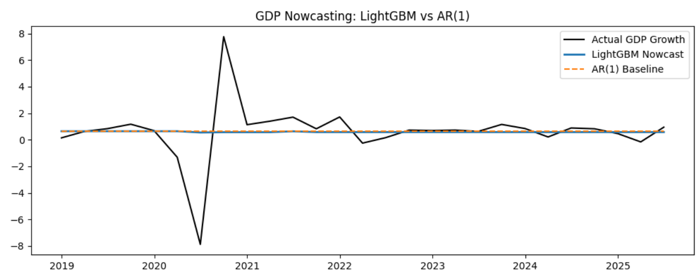
Empirically, however, the gradient boosting approach shows limited predictive power in this macroeconomic setting. Despite its theoretical flexibility, LightGBM fails to outperform the simple AR(1) benchmark, suggesting that the relatively small sample size and high noise in monthly indicators hinder its ability to learn stable nonlinear patterns. We therefore turn to recurrent neural networks (RNNs) to explicitly model temporal dependencies. Nonetheless, direct RNN forecasting also underperforms the AR(1) model. To enhance performance, we adopt a residual-learning framework: the AR(1) model captures the linear dynamics of GDP growth, while an RNN is trained on its residuals to model remaining nonlinear components. This hybrid AR(1)RNN approach yields improved out-of-sample accuracy and more stable nowcasts, demonstrating the complementary strengths of statistical and neural network models in capturing macroeconomic dynamics.

7.3 LightGBM results and limitations

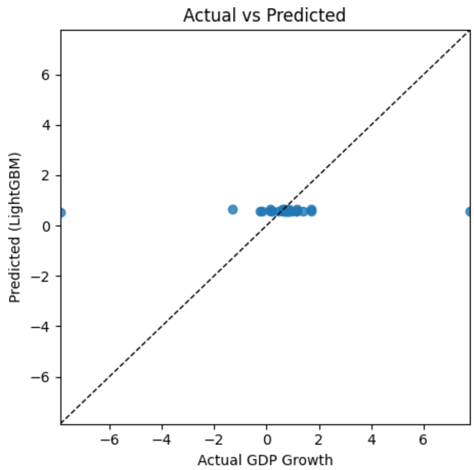
To assess the predictive capacity of gradient boosting in the nowcasting context, a LightGBM model was first estimated using quarterly GDP growth as the dependent variable and monthly macroeconomic indicators as predictors. Initial experiments employed a baseline specification with 400 trees, a learning rate of 0.05, and 15 leaves per tree. To further explore model capacity, a grid search was conducted over key hyperparameters, including the number of leaves, learning rate, minimum child samples, feature and bagging fractions, and regularization terms (λ_1, λ_2).



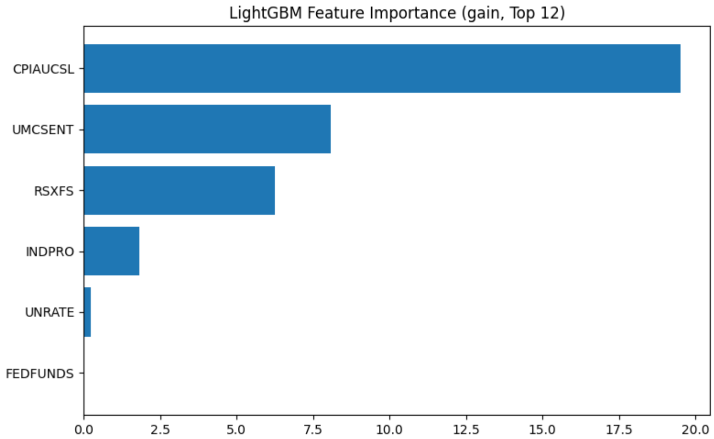
(a) LGBM Model Comparison 1



(b) LGBM Model (best fits)



(a) Actual vs Predict



(b) Feature Importance

Figures above illustrate the models performance. Despite tuning efforts, the LightGBM nowcasts closely track the mean of GDP growth and fail to capture cyclical fluctuations, as evident from the flat predictions relative to the actual series and the low dispersion in the actualpredicted scatter plot. Feature importance results suggest that variables such as consumer prices (CPIAUSCL), consumer sentiment (UMCSENT), and retail sales (RSXFS) contribute most to the model, but their combined signal is insufficient for meaningful short-term GDP inference.

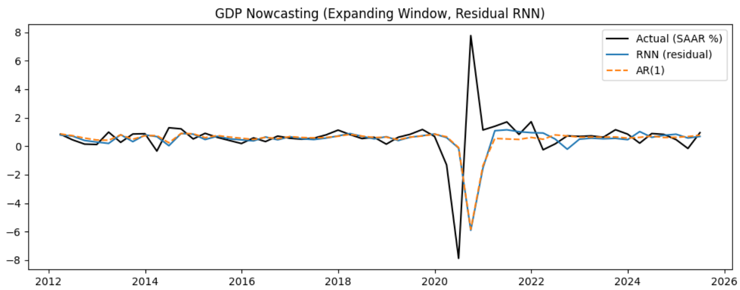
These findings indicate that tree-based ensemble methods, while flexible, struggle to extract robust predictive patterns from a limited macroeconomic sample with high noise and mixed frequencies. Consequently, subsequent analysis focuses on recurrent neural networks (RNNs), which are better suited to capture temporal dependencies and nonlinear dynamics in sequential data.

To address strong temporal dependence and mixed-frequency signals in a small sample, I estimate a residual RNN that augments an AR(1) benchmark:

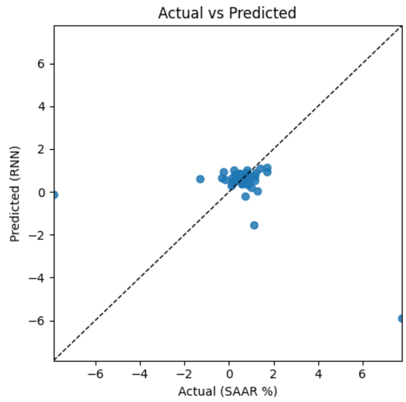
$$y_t \;=\; \phi\, y_{t-1} \;+\; f_\theta(\mathbf{x}_{1:t}) \;+\; \varepsilon_t,$$

where y_t is quarterly real GDP growth (SAAR%), ϕy_{t-1} captures inertial dynamics, and $f_\theta(\cdot)$ is a compact recurrent block fed with the withinquarter stream of monthly indicators. I use an expanding window for re-estimation each quarter. This residual formulation keeps the linear meanreversion in the baseline and lets the RNN focus on nonlinear, time-varying structure; when monthly signals are weak, the correction term shrinks toward zero, yielding stable nowcasts.

Figure 10 overlays the residual RNN nowcasts on the realized series (left) and shows the actualpredicted scatter (right). Relative to tree ensembles, the RNN tracks quarter-to-quarter swings more closely and avoids the severe mean-reversion bias; outside the extreme pandemic quarters, deviations are modest and centered near the 45 line. The improvement comes from exploiting sequential dependence across monthly releases rather than treating them as exchangeable features.



(a) GDP Nowcasting



(b) Actual vs. Predicted (Residual RNN)

Figure 10: Residual RNN nowcasting performance. Left: expanding-window out-of-sample paths versus realized GDP growth (SAAR%). Right: scatter around the 45 line indicates reduced bias and tighter dispersion outside pandemic outliers.

For macro nowcasting with limited quarterly targets and noisy monthly flows, a residual RNN is a better default than tree-based gradients: it preserves a transparent AR backbone, adds parsimonious nonlinear updates from the information flow, and remains stable under expanding-window re-estimation. Subsequent sections therefore build on this RNN specification.

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