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Real-Time Monitoring of U.S. Business Cycles via MFD-FM Methodology

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Abstract

The objective of this study is to develop a real-time monitoring framework for U.S. business-cycle dynamics using a Mixed-Frequency Dynamic Factor Model (MFD-FM). The methodology combines quarterly GDP with monthly macroeconomic indicators, inflation (CPI), interest rate, housing price index (HPI), and labor force participation rate (LFPR), within a state-space representation estimated through the Kalman filter, producing a latent common factor that summarizes aggregate economic activity. Results indicate that the extracted factor captures cyclical shifts and anticipates downturn and recovery phases associated with recent shocks. The framework is recommended as a macroeconomic surveillance tool to support decision-making under uncertainty. As a limitation, further validation is required across alternative indicator sets and different national contexts, implying possible adjustments for structural breaks and data availability constraints. Originality lies in providing an operational mixed-frequency implementation aimed at real-time cycle monitoring. It is concluded that the proposed MFD-FM approach offers a useful and replicable alternative for timely business-cycle tracking.

JEL Classification: C32, C53, E32
Keywords: Business cycles, Nowcasting, Dynamic factor model, Mixed-frequency data, Kalman filter.

Monitoreo en Tiempo Real de los Ciclos Económicos de Estados Unidos mediante la Metodología MFD-FM

Resumen

El objetivo de este estudio es desarrollar un esquema de monitoreo en tiempo real del ciclo económico de Estados Unidos mediante un Modelo de Factores Dinámicos de Frecuencias Mixtas (MFD-FM). La metodología integra el PIB trimestral con indicadores macroeconómicos mensuales (inflación (CPI), tasa de interés, índice de precios de vivienda (HPI) y tasa de participación laboral (LFPR)) en una formulación de espacio de estados estimada con el filtro de Kalman, a partir de la cual se obtiene un factor común representativo de la actividad económica agregada. Los resultados muestran que el factor captura los cambios cíclicos y anticipa episodios de contracción y recuperación asociados a shocks recientes. El enfoque puede emplearse como herramienta de vigilancia macroeconómica y apoyo a la toma de decisiones bajo incertidumbre. Como limitación, se requiere validación adicional bajo distintos conjuntos de variables y contextos nacionales, lo que implica potenciales ajustes por quiebres estructurales y disponibilidad de datos. La originalidad del trabajo radica en su implementación operativa para seguimiento del ciclo económico con información de frecuencia mixta. Se concluye que el MFD-FM constituye una alternativa útil y replicable para el monitoreo oportuno del ciclo económico.

Clasificación JEL: C32, C53, E32

Palabras clave: Ciclos económicos, Nowcasting, Modelo de factores dinámicos, Datos de frecuencia mixta, Filtro de Kalman

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1. Introduction

In the 21st century, global economies have faced a series of events that have led to high volatility and rapid changes in the economic environment. Financial crises, pandemics, and geopolitical conflicts have altered economic stability and growth, affecting the capacity of countries to formulate effective policies and make well-informed decisions. Given these challenges, the ability to monitor the economy in real time has become a fundamental requirement. Traditional economic analysis models have limitations because they rely on data with fixed frequencies and late revisions. Consequently, advanced tools such as Mixed-Frequency Dynamic Factor Models (MFD-FM) have emerged, which integrate information at different frequencies and allow for dynamic estimates as new data appears (Stock & Watson, 2002).

In an increasingly interconnected global environment, the effects of any economic event spread quickly, making ever more difficult for countries to remain independent of external influences. As Borio (2014) points out, financial and trade dependence amplifies the impact of crises and changes in government policies, complicating the precise identification of the causes of economic problems. In this scenario, the capacity to respond to crises depends on access to accurate, up-to-date information. Models such as the MFD-FM enable us to draw a distinction between timely policy responses and those that come too late, making them crucial tools for economic stability and crisis prevention. A clear example of the need for dynamic models occurred during the 2007–2008 financial crisis, when traditional approaches could not foresee the severity of the economic collapse. In contrast, models that utilized real-time updates were better able to predict the economic deterioration, resulting in more effective policy responses (Reinhart & Rogoff, 2009). This demonstrates that incorporating high-frequency data and continuously updating estimates can significantly improve economic forecasts and crisis-mitigation strategies.

Technological advances have enabled significant progress in the collection and analysis of economic data. It is now possible to process large volumes of information in real time, which strengthens the predictive capacity of econometric models and improves their applicability in financial decision-making (Bailey, 2020). Thanks to these advances, economists can work with data that were previously inaccessible or took too long to process, thereby increasing the accuracy and relevance of economic forecasting models (Koopman et al., 1999).

This study focuses on applying the MFD-FM model to analyze U.S. economic cycles and assess its usefulness in economic and financial decision-making. The research seeks to determine whether these models can incorporate high-frequency data and continuously update estimates in an environment characterized by uncertainty and unexpected shocks. Additionally, explores the implementation of the MFD-FM in the context of a U.S. recession, providing valuable empirical insights for future research and applications in economics and finance.

2. Theoretical Framework

2.1. Mixed-Frequency Dynamic Factor Models (MFD-FM)

In the current century, world economies have been subject to events generating significant volatility and rapid changes in the global economic environment. In this context, the integration of multiple data sources and the ability to update estimates in real time have become crucial for obtaining a precise and current view of the state of the economy. Mixed-Frequency Dynamic Factor Models (MFD-FM) have become essential tools because of their ability to handle data of different frequencies and their flexibility in incorporating new data as they become available.

State-space models describe dynamic systems in which observable variables are determined by unobservable (state) factors that evolve over time. Because of their versatility, these models are highly useful in various applications, such as analyzing cyclical fluctuations and economic growth trends, or examining volatility dynamics in financial markets (Harvey, 1990; Stock & Watson, 1991). A central component of state-space models is the Kalman Filter, which efficiently estimates unobservable states in real time (Durbin & Koopman, 2012; Kalman, 1960). A key aspect of the theory, discussed in Peña and Box (1987), focuses on how to simplify complex data structures consistently into a smaller number of factors. This is very practical and can be applied to diverse problems related to dimensionality reduction and the analysis of multivariate time series. The methodology relates to that proposed by Hu and Chou (2003), providing a framework for simplifying and restructuring complex data into fewer factors in a dynamic factor model.

An important step in this direction was combining the state-space framework with dynamic factor models (see Doz et al., 2011; Forni et al., 2000). By uniting these two methodologies, it is possible to estimate unobserved Common Factors that affect multiple time series. The Common Factors, as noted earlier, are extracted from time series and improve forecast accuracy while uncovering the underlying dynamics governing economic processes.

The MFD-FM model is especially relevant in this context because it can combine data with different sampling frequencies—such as quarterly and monthly—to provide estimates or forecasts of the variables involved. Each time new data arrives, whether monthly or quarterly, the model updates itself, allowing for continuous real-time revision of estimates. This continuous updating capability is crucial for making informed, timely decisions in economic policy and financial management (Giannone et al., 2008). The importance of these models cannot be understated. The Common Factor enables better integration of available information by capturing variations shared among different economic indicators. On the one hand, this approach improves the accuracy of forecasts; on the other, it provides a valuable foundation for interpreting economic outcomes.

Therefore, identifying and estimating Common Factors is crucial for enhancing the precision and usefulness of economic forecasts. The ability to work with data of different frequencies and to update estimates continuously underscores the relevance of models such as the Mixed-Frequency Dynamic Factor Model for economic forecasting (Aruoba et al., 2011; Giannone et al., 2008). These attributes help develop a deeper understanding of economic dynamics to facilitate better management.

2.2. State-Space Models

State-space models constitute a category of statistical tools designed to represent dynamic systems in which observable variables are conditioned by unobservable (state) factors that evolve over time (Durbin & Koopman, 2012). In economics, these models are particularly useful for analyzing time series, as they facilitate the study of dynamic economic phenomena—such as business cycles or growth trends—that cannot be directly observed (Harvey, 1990).

One of the most significant strengths of these models is the ability to update estimates as new data becomes available, making them an integral tool for real-time economic monitoring (Doz et al., 2011). Furthermore, they can represent dynamic systems in which some of the observable variables are influenced by a non-observable component that may change over time. Stock and Watson (2002) were among the first to use these models to identify Common Factors that explain similarities among several variables, as well as idiosyncratic factors that capture the specific dynamics of each variable.

2.3. Kalman Filter

The Kalman Filter can be described as an algorithmic technique used to produce estimates of unobservable states in a state-space model. Although the concept was first developed for control processes and engineering, its effectiveness has recently led to its adoption in economics to produce optimal estimates even when data are noisy or incomplete (Kalman, 1960; Durbin & Koopman, 2012). When applied to economic models, the filter allows for real-time updates of information and errors as new data arrive, thereby improving estimation accuracy.

2.4. Nowcasting

Nowcasting refers to the practice of predicting the current state of the economy using statistical models that incorporate real-time data. Over the last decade, this technique has become increasingly popular, especially among central banks and financial institutions, due to the growing challenge of making well-founded decisions in a constantly evolving economic environment (Bańbura et al., 2011). Stundziene et al. (2023) provides a comprehensive overview of research utilizing NowCasting. Recent research indicates that new approaches to incorporating high-frequency data and integrating multiple data sources can be particularly effective in improving model accuracy—both for identifying the current state of the economy and for predicting future trends. For example, as shown in Giannone et al. (2008), when based on state-space models and the Kalman Filter, Nowcasting frameworks can rapidly adjust to newly available data, facilitating real-time forecasting. Proietti et al. (2021) state that only a few indicators matter when nowcasting the short-term level of aggregate economic activity. Furthermore, the predictive power of indicators depends on economic circumstances (Gilbert et al., 2017). Moreover, the principal economic indicators are typically published on a monthly or quarterly basis. Among these, Gross Domestic Product (GDP) stands out as the most significant variable for analyzing economic cycles. However, GDP is not only released on a quarterly schedule but is also subject to a reporting lag, which can present challenges for timely economic analysis.

2.5. Business Cycles

Traditional nowcasting approaches have made significant advancements, in recent decades, new methodologies incorporating advanced technologies such as artificial intelligence (AI) and machine learning have emerged. These more recent approaches promise greater accuracy and adaptability in predicting economic and financial cycles. Given the relevance of economic and financial cycles, numerous studies have been conducted to contextualize and analyze cycles through economic and financial indicators that reflect the performance of countries, thus supporting cycle analysis

(Tenreiro Machado, Duarte, & Duarte, 2012; Cantú Esquivel, Ríos Bolívar, & Jiménez Preciado, 2023). In this context, the National Bureau of Economic Research (NBER) stands out as the organization responsible for determining the start and end of recessions and expansions in U.S. economic activity. In Mexico, the National Institute of Statistics and Geography (INEGI) publishes the System of Composite Indicators: Coincident and Leading (SICCA), a series of indicators that allow for detailed monitoring of the country's economic activity performance. SICCA integrates key variables that help anticipate the direction of the national economy and is considered a faithful reflection of Mexico's economic cycles (Heath, 2012). Both NBER and INEGI employ traditional methodologies for determining economic cycles.

In recent decades, two prominent methodological trends have emerged for the study of economic and financial cycles. While it is argued that the results of these methodologies have been satisfactory (Sun et al., 2025), their application in governmental and financial agencies remains limited. These trends include traditional econometric methods and, more recently, those based on artificial intelligence (AI), machine learning, and big data analysis. Traditional econometric methods include models such as autoregressive integrated moving average (ARIMA), vector autoregression (VAR), and linear regression (Cepni et al., 2019; Dai et al., 2024; Wang & Xiao, 2023; Zhang et al., 2024). However, these models present significant limitations when forecasting economic indicators (Griliches, 1974; Inoue & Kilian, 2006; Stock & Watson, 1999), as their linearity assumptions fail to capture the true relationships between indicators, which do not conform to these assumptions. Additionally, they tend to overestimate the heteroscedasticity of economic indicators, resulting in inadequate predictions (Sun et al., 2025).

In the last decade, the number of studies focused on predicting economic and financial cycles using machine learning and data science models has increased. These models have generally shown to be more effective than traditional methods in forecasting cycle trends. For example, Pontes et al. (2024) highlight the ability of three machine learning models—Multinomial Logistic Regression (MLR), Support Vector Machines (SVMs), and Multi-layer Perceptron (MLP)—to analyze the state of the economy based on predictions of the four phases of the economic cycle (expansion, peak, contraction, and recession), with a comparative approach between the economies of the U.S. and the Eurozone. Pontes et al. (2024) introduce a sentiment analysis index using news analysis as an additional variable to support traditional forecasting models for predicting economic cycles. The uncertainty index complements the results of quantitative models, including a sentiment index based on relevant variables selected by a Bayesian LASSO model and optimized by a Multi-objective Lechtenger Algorithm (MOLA). Yang et al. (2025) presents an AI algorithm, Bi-LSTM, combined with the design of a data processing structure for key indicators, arguing that this model, by analyzing sentiment in news, can anticipate economic cycles. This model uses both quantitative and qualitative data from news narratives. In general, these models show challenges in their interpretation, from the way they reach predefined results (Varian, 2014) to understanding the intrinsic relationships between the variables used. The process of interpreting the results of a model not only enhances the credibility of their results but also their acceptance and practical applicability. The main advantage of the proposed models lies in their adaptability to changes in their environment, which is reflected in the transformation of the relationships between the variables used. Therefore, not only are changes in economic or financial cycles identified, but also modifications in the relationships between the variables employed in each phase of an economic cycle.

3. Methodology

3.1. Macroeconomic Data

Five key macroeconomic indicators for the United States are considered, selected for their relevance in assessing economic health and their systemic interactions. Researchers have found this model to be valid and effective for extracting hidden factors from a limited group of economic indicators, as shown by studies like Delajara and Hernandez (2016), Mariano and Murasawa (2003), Camacho and Peréz-Quiróz (2010), Aruoba and Diebold (2011); Additionally, Stundziene et al. (2023) provides a comprehensive overview of research utilizing NowCasting.

3.2. Key Macroeconomic Variables

The Interest Rate (IR) in the United States, determined by the Federal Reserve (Fed), plays a central role in influencing the cost of credit and overall economic activity. The Labor Force Participation Rate (LFPR), published by the Bureau of Labor Statistics (BLS), reflects the proportion of the working-age population that is actively participating in the labor market. The Consumer Price Index (CPI), also released monthly by the BLS, serves as a key measure of inflation. The House Price Index (HPI), issued monthly or quarterly by the Federal Housing Finance Agency (FHFA), tracks changes in residential real estate prices. Lastly, the Gross Domestic Product (GDP) is a quarterly indicator that captures the overall growth and performance of the U.S. economy. The periodicity of these indicators, essential for designing the mixed-frequency model, is summarized in Table 1 below.

Table 1. Periodicity of macroeconomic indicators used in the mixed-frequency model[2]:

Indicator	Published By	Frequency
Interest Rate	Determined by FOMC (Federal Reserve)	Eight times a year
Labor Force Participation Rate	Bureau of Labor Statistics (BLS)	Monthly
House Price Index	Federal Housing Finance Agency (FHFA)	Quarterly (with monthly reports)
Consumer Price Index	Bureau of Labor Statistics (BLS)	Monthly
Gross Domestic Product	Bureau of Economic Analysis (BEA)	Quarterly
NBER-date recessions	Determined by National Bureau of Economic Research (NBER)	Not regularly scheduled (published retrospectively)

Note. All series are seasonally adjusted. Year-over-year transformations are applied to ensure comparability.

3.3. Econometric Model: Mixed-Frequency Dynamic Factor Model (MFD-FM)

The MFD-FM allows integration of series with different frequencies (e.g., quarterly GDP and monthly indicators) and handles missing data, capturing their co-movement through a latent factor f_t that

[2] This model employs seasonally adjusted series. Our software first calculates year-on-year differences to adjust for seasonality

represents the economic cycle. This approach follows the literature of Aruoba and Diebold (2010), among others, and has been validated for real-time analysis.

3.4. Model Specification

1. Measurement Equation: Relates the observed variables ($\boldsymbol{y_{N,t}}$) to the Common Factor ($\boldsymbol{f_t}$) and idiosyncratic components ($\boldsymbol{v_{n,t}}$):

$$\begin{pmatrix} \boldsymbol{y_{1,t}} \\ \boldsymbol{y_{2,t}} \\ \boldsymbol{y_{3,t}} \\ \vdots \\ \boldsymbol{y_{N,t}} \end{pmatrix} = \begin{pmatrix} \boldsymbol{\gamma_1\left(\frac{1}{4}f_t + \frac{2}{4}f_{t-1} + \frac{3}{4}f_{t-2} + f_{t-3} + \frac{3}{4}f_{t-4} + \frac{2}{4}f_{t-5} + \frac{1}{4}f_{t-6}\right)} \\ \boldsymbol{\gamma_2 \sum_{j=0}^{11} f_{t-j}} \\ \boldsymbol{\gamma_3 \sum_{j=0}^{11} f_{t-j}} \\ \vdots \\ \boldsymbol{\gamma_N \sum_{j=0}^{11} f_{t-j}} \end{pmatrix}$$

$$+ \begin{pmatrix} \frac{1}{4}\nu_{1,t} + \frac{2}{4}\nu_{1,t-1} + \frac{3}{4}\nu_{1,t-2} + \nu_{1,t-3} + \frac{3}{4}\nu_{1,t-4} + \frac{2}{4}\nu_{1,t-5} + \frac{1}{4}\nu_{1,t-6} \\ \nu_{2,t} \\ \nu_{3,t} \\ \vdots \\ \nu_{N,t} \end{pmatrix} \quad (1)$$

- GDP ($\boldsymbol{y_{1,t}}$): The factor is averaged on a quarterly basis with temporal weights.
- Monthly indicators ($y_{2,t}, \dots, y_{N,t}$): The factor is aggregated over 12-month moving windows.

2. Dynamics of the Factor and Idiosyncratic Terms: The second equation, known as the transition equation, describes how the Common Factor (f_t) evolves over time via an autoregressive process that captures its dependence on past values and reflects the system's fundamental dynamics:

$$f_t = \phi_1 f_{t-1} + \phi_2 f_{t-2} + \cdots + \phi_P f_{t-P} + e_t \quad e_t \sim N(0,1) \quad (2)$$

$$\nu_{n,t} = \phi_{1n}\nu_{n,t-1} + \cdots + \phi_{Qn}\nu_{n,t-Q} + \epsilon_{n,t}, \quad \epsilon_{n,t} \sim N\left(0, \sigma^2_{\epsilon_n}\right) \quad (3)$$

3. Estimation via the Kalman Filter: The model is expressed in state-space form, enabling the estimation of $\boldsymbol{f_t}$ and parameters via maximum likelihood. The Kalman Filter handles missing data without arbitrary imputation, updating estimates as new data arrives. This facilitates real-time identification of the economic cycle ($\boldsymbol{f_t}$), which is crucial for economic policymaking.

4.Results

4.1. Period Definition and Economic Context

The evolution of the Common Factor throughout the current century is analyzed by dividing the study into two key periods. The first spans from January 2003 to December 2013, a period that includes the Subprime Mortgage Crisis (December 2007 to June 2009). The second period, extending from January 2014 to March 2024, covers critical events such as the outbreak of the COVID-19 virus (February 2020) and the onset of the Ukraine–Russia conflict (February 2022). According to the National Bureau of Economic Research (NBER), the periods of expansion and contraction of the U.S. economy during this century.

4.2. Phase 1: 2003–2013 — Subprime Mortgage Crisis and Early Recovery.

NBER Dating and the Common Factor during the Subprime Crisis.

Between 2003 and 2013, the Common Factor began to fall in late 2004, ahead of the official start of the Subprime crisis declared by the NBER (December 2007). Throughout the recession, the Common Factor continued to reflect economic strains and showed an initial recovery somewhat earlier (approximately 3 to 4 months) than the official end date of the recession (June 2009). As illustrated in Figure 1, although some temporal lags appeared relative to NBER dates, the Common Factor confirmed its usefulness as a leading indicator, sensitive to economic policy measures and able to capture signs of contraction and expansion.

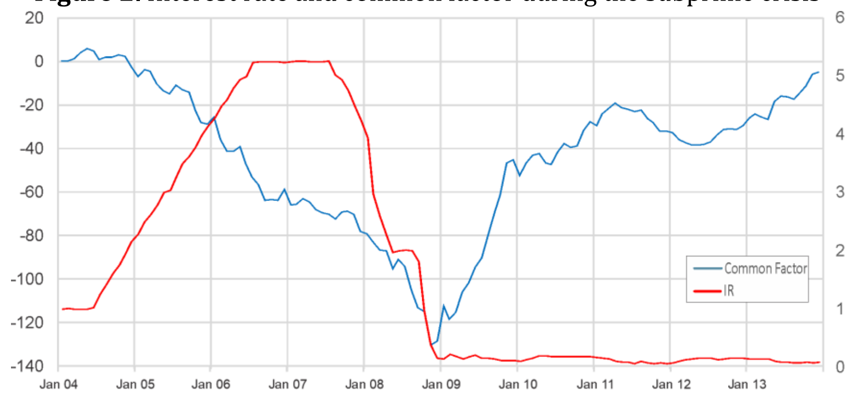
Figure 1. Common factor and NBER-dated recessions

Note. The figure displays the estimated common factor alongside the NBER-defined recession periods, covering the time span from January 2004 to late 2013. The shaded areas represent the official recession dates identified by the National Bureau of Economic Research (NBER). Author's own calculations.

Interest Rate vs. the Common Factor during the Subprime Crisis.

From 2004 to 2006, the interest rate evolved invers to the Common Factor: the rate rose just as the Factor declined; starting in 2007, coinciding with the Factor's deterioration, the rate began to fall and eventually reached zero in 2008. Subsequently, the Common Factor indicated an economic cycle recovery while the interest rate remained at historically low levels. As shown in Figure 2, this highlights that, although monetary policy can delay a contraction, it cannot entirely prevent it when economic conditions are sufficiently adverse. It also underscores the necessity of considering additional factors that drive recovery beyond the interest rate.

Figure 2. Interest rate and common factor during the subprime crisis

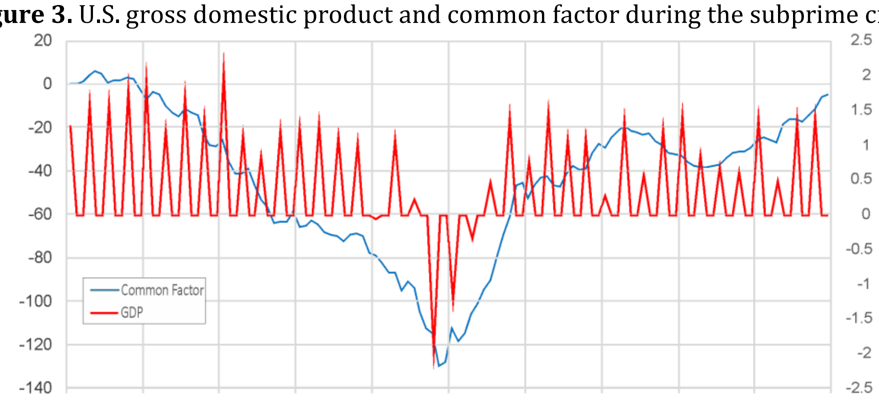


Note. The figure compares the evolution of the U.S. interest rate and the estimated common factor. It illustrates the divergence between monetary policy and underlying economic momentum, particularly during the crisis and early recovery phase. Author's own calculations.

Behavior of Gross Domestic Product vs. the Common Factor during the Subprime Crisis.

U.S. GDP and the Common Factor evolved in synchronously between 2005 and 2008, with GDP mirroring, though less abruptly, the contraction phase captured by the Common Factor. However, the Common Factor recorded a steeper decline and recovered more steadily than GDP. The latter exhibited more volatile cycles because of specific quarterly influences, whereas the Common Factor offered a more aggregated and persistent view of the crisis. As illustrated in Figure 3, while GDP is a key production indicator, the Common Factor provides clearer, earlier, and broader signals about economic health.

Figure 3. U.S. gross domestic product and common factor during the subprime crisis

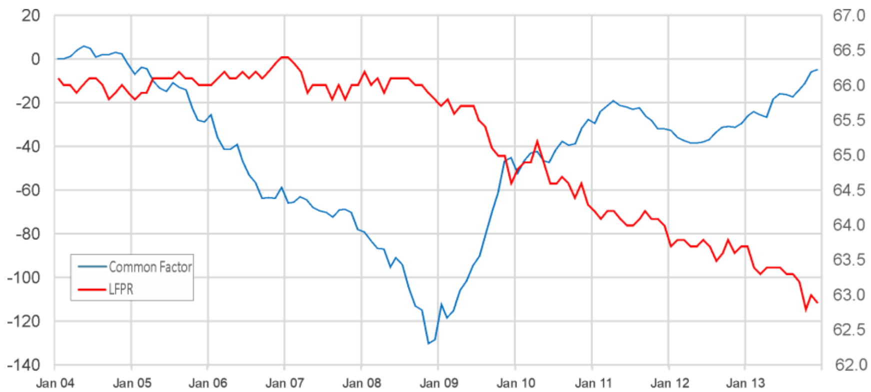


Note. The figure compares the trajectory of U.S. gross domestic product (GDP) and the estimated common factor. While both series reflect the contraction during the subprime crisis, the common factor shows a more pronounced decline and a smoother recovery, capturing broader macroeconomic dynamics beyond production alone. Author's own calculations.

Behavior of the Labor Force Participation Rate (LFPR) vs. the Common Factor during the Subprime Crisis.

The LFPR remained stable until August 2008, lagging behind the Factor's contraction. Once the LFPR began to drop, it did so continuously, even after the Factor started its recovery phase. As shown in Figure 4, this lag indicates that the labor market was slower to rebound, possibly because of structural factors (population aging or changes in labor composition). The persistent decline in LFPR suggests that, while the broader economy (captured by the Common Factor) was improving, the labor sector remained under pressure for a longer period.

Figure 4. Labor force participation rate and common factor during the subprime crisis

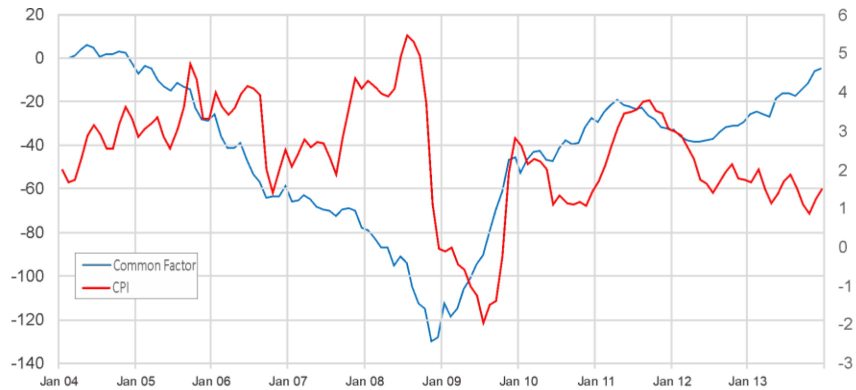


Note. The figure compares the evolution of the labor force participation rate (LFPR) and the estimated common factor during and after the subprime crisis. It highlights the delayed and prolonged downturn in labor market participation relative to the broader economic recovery, suggesting structural challenges in employment dynamics. Author's own calculations.

Behavior of the Consumer Price Index (CPI) vs. the Common Factor during the Subprime Crisis.

The CPI increased from 2004 to 2006, indicating inflationary pressures, while the Common Factor was already in decline. By the end of 2008, the CPI reached its peak, and the Common Factor was at its lowest, reflecting the height of the crisis. As illustrated in Figure 5, afterwards, both began to recover, but the Common Factor did so more quickly and steadily, whereas the CPI was slower to return to previous levels. The study concludes that while the CPI is sensitive to price fluctuations, the Common Factor captures broader economic trends and serves as a more comprehensive indicator of contraction and subsequent expansion.

Figure 5. Consumer price index and common factor during the subprime crisis

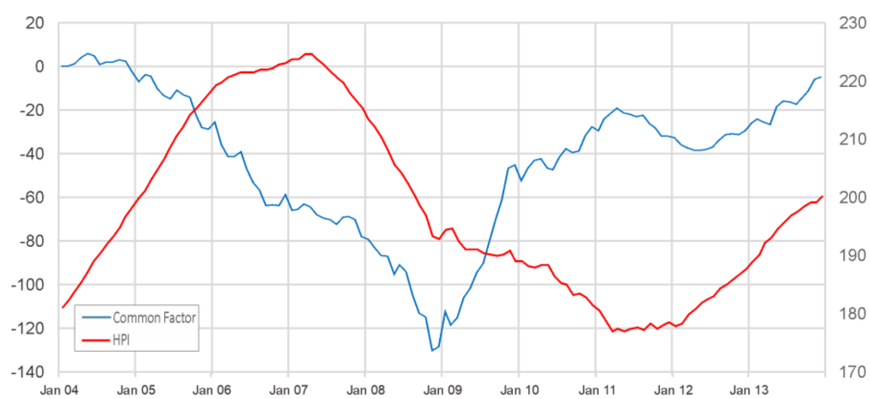


Note. The figure compares the trajectory of the consumer price index (CPI) and the estimated common factor during and after the subprime crisis. While the CPI reflects short-term inflation dynamics, the common factor provides a broader and smoother representation of macroeconomic conditions, particularly during periods of contraction and recovery. Author's own calculations.

Behavior of the House Price Index (HPI) vs. the Common Factor during the Subprime Crisis.

Finally, regarding the HPI, it rose steadily until March 2007, even as the Common Factor declined, indicating a possible "housing bubble" disconnected from the broader economic slowdown. Once the crisis hit in 2008, the HPI fell sharply, in synchrony with the severe decline of the Common Factor. As shown in Figure 6, it subsequently recovered, although the HPI did so gradually. Thus, the real estate market can behave out of step with the rest of the economy and was a key factor in explaining the depth and duration of the Subprime crisis, influencing both the contraction and the subsequent global recovery.

Figure 6. *Housing price index and common factor during the subprime crisis*



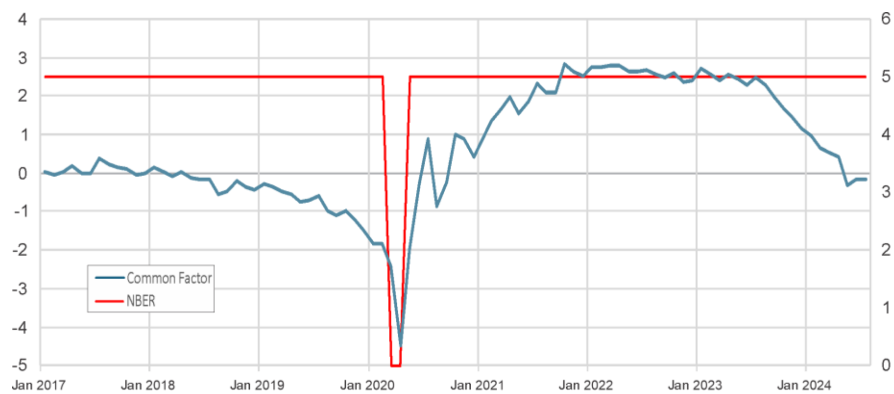
Note. The figure compares the evolution of the housing price index (HPI) and the estimated common factor over the subprime crisis period. It highlights the early divergence between housing prices and overall economic conditions, the sharp decline during the crisis, and the slower recovery of the real estate market relative to broader macroeconomic dynamics. Author's own calculations.

4.3. Phase 2: 2014–2024 — The COVID-19 Pandemic, the Ukraine–Russia War, and Economic Adjustments in the United States

Relationship between NBER Dating and the Common Factor during the COVID-19 Crisis

In this period (2017–2024), the NBER recognized a short-term recession caused by COVID-19 and an expansion through mid-2024. The Common Factor proved to be a leading indicator, anticipating the economic contraction before the official NBER declaration and also signaling the recovery phase once the health crisis had subsided. According to NBER specialists, the Ukraine–Russia conflict had a more moderate, delayed effect, not triggering a financial crisis in the U.S. However, from the second half of 2022 onward, the Common Factor showed a slight contraction that may reflect mounting economic tensions (see Figure 7).

Figure 7. *Common factor and NBER-dated recession periods during the COVID-19 crisis*

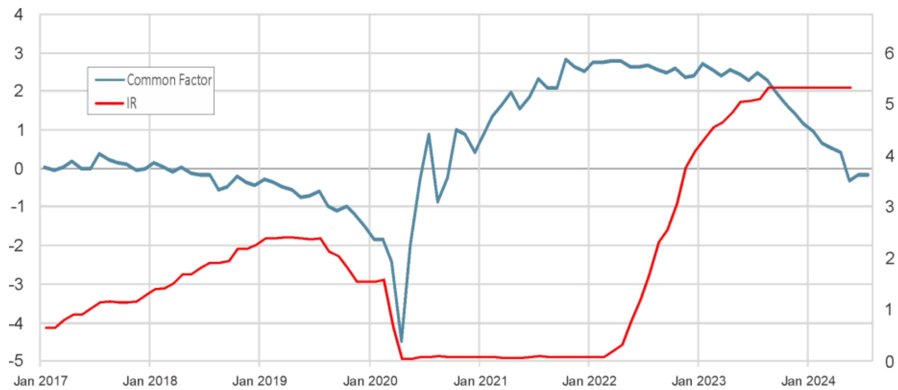


Note. The figure illustrates the relationship between the estimated common factor and the NBER-dated recession associated with the COVID-19 pandemic. It shows how the common factor anticipated both the onset of the recession and the subsequent recovery phase. It also reflects the moderate and delayed economic impact of the Ukraine–Russia conflict starting in 2022. Author's own calculations.

Behavior of the Interest Rate (IR) vs. the Common Factor during the COVID-19 Crisis.

The interest rate had a moderately upward trend from 2017 to 2019. Starting in July 2019, however, the Federal Reserve drastically reduced the rate to support the economy in the face of COVID-19. Although this did not prevent the Factor's decline, it did help stimulate the subsequent recovery. At the beginning of 2022, the Fed again raised rates to control inflation, coinciding with an additional slight drop in the Common Factor. Toward the end of 2022 and the start of 2023, interest rates reached their highest point, and the Common Factor showed signs of cooling, possibly due to accumulated pressures and monetary tightening (see Figure 8).

Figure 8. *Interest rate and common factor during the COVID-19 crisis*

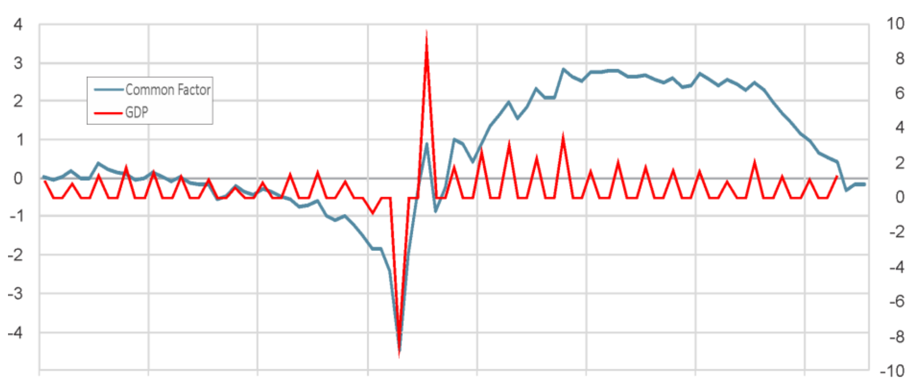


Note. The figure shows the evolution of U.S. interest rates alongside the estimated common factor during the COVID-19 crisis. It highlights the Federal Reserve's rate cuts at the onset of the pandemic and the subsequent increases to control inflation, with corresponding movements in the economic cycle. Author's own calculations.

Behavior of GDP vs. the Common Factor during the COVID-19 Crisis.

Between February and July 2020, GDP experienced abrupt fluctuations, coinciding with the start and end of the COVID-19 recession. The Common Factor also reflected these movements in a synchronized manner, capturing the immediate impact of events like the pandemic and the conflict in Ukraine. Although GDP recovered quickly following the health crisis, the Common Factor showed a steadier but slower recovery. GDP fluctuations were more pronounced—likely because of its quarterly periodicity and distinct one-off influences—while the Common Factor captured more gradual changes (see Figure 9).

Figure 9. *U.S. gross domestic product and common factor during the COVID-19 crisis*

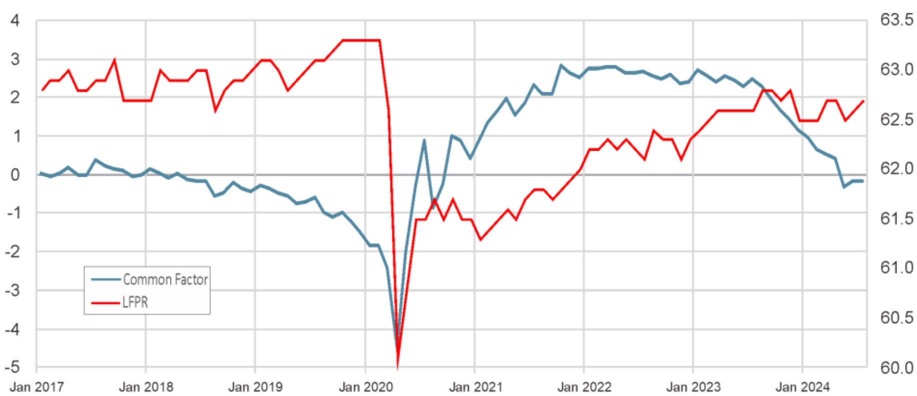


Note. The figure compares quarterly fluctuations in U.S. gross domestic product (GDP) with the smoother dynamics of the estimated common factor during the COVID-19 crisis. It captures the immediate impact of the pandemic and subsequent shocks, as well as differences in the speed of recovery between both series. Author's own calculations.

Behavior of the Labor Force Participation Rate (LFPR) vs. the Common Factor during the COVID-19 Crisis.

The LFPR remained stable before COVID-19 but dropped sharply at the start of 2020 due to the pandemic. Although it began to recover, it never returned to pre-pandemic levels, indicating that some workers had left the labor market for structural or personal reasons. Meanwhile, the Common Factor also declined in the worst phase of the crisis, though it recovered more steadily. By the end of the period, the LFPR was still below its pre-pandemic level, and the Common Factor showed signs of a slowdown (see Figure 10).

Figure 10. Labor force participation rate and common factor during the COVID-19 crisis

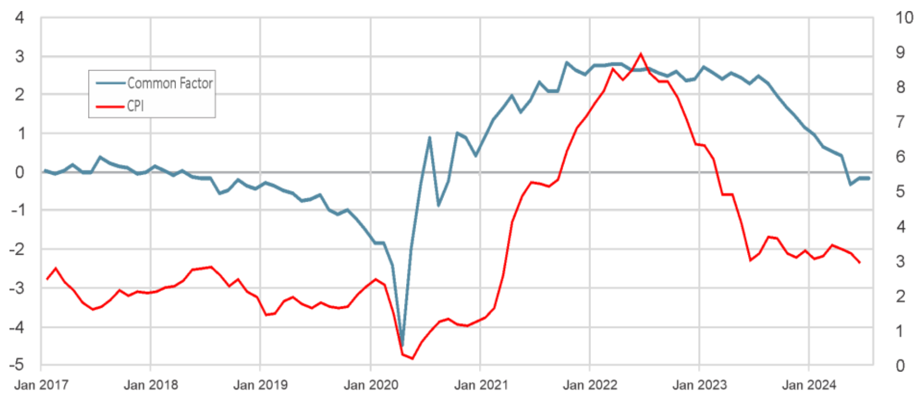


Note. The figure compares the evolution of the labor force participation rate (LFPR) and the estimated common factor during the COVID-19 crisis. It highlights the sharp decline in labor market participation during the pandemic and its incomplete recovery, contrasted with the steadier improvement in broader economic conditions captured by the common factor. Author's own calculations.

Behavior of the Consumer Price Index (CPI) vs. the Common Factor during the COVID-19 Crisis.

Before 2019, both the CPI and the Common Factor were relatively stable, indicating a scenario of controlled prices and low inflationary pressure. Both dropped notably in early 2020 with the onset of the pandemic. Subsequently, they rose until mid-2022, driven by the resurgence of demand and the reconfiguration of supply chains. After reaching their peak, both fell from July 2022 onward, partly because of inflation-control policies and the start of the Russia–Ukraine war (see Figure 11).

Figure 11. Consumer price index and common factor during the COVID-19 crisis

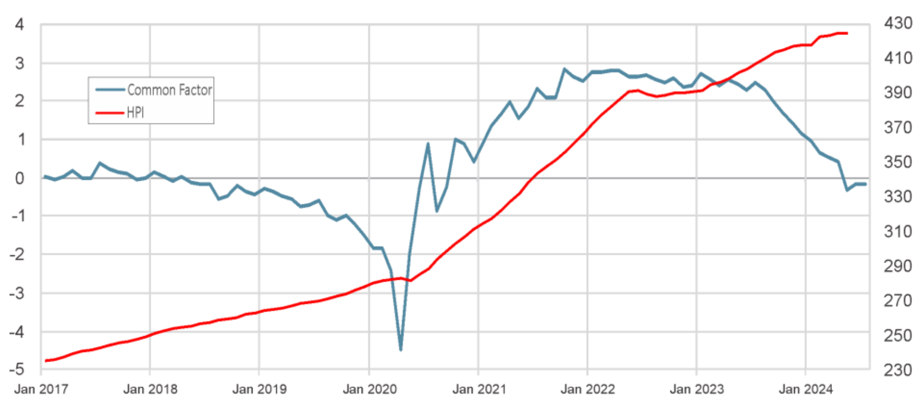


Note. The figure illustrates inflation dynamics through the consumer price index (CPI) in relation to the estimated common factor during the COVID-19 crisis. It shows the sharp decline at the onset of the pandemic, followed by a strong rebound and subsequent moderation, reflecting the effects of inflation control policies and geopolitical tensions. Author's own calculations.

Behavior of the House Price Index (HPI) vs. the Common Factor during the COVID-19 Crisis.

The HPI maintained steady growth throughout the period, with only brief slowdowns during the pandemic and the beginning of the war in Ukraine—no significant drops occurred. The Common Factor, by contrast, showed greater volatility. The robustness of the real estate market may have been helped by low interest rates and high housing demand. However, constant increases in the HPI, among economic tensions, increase concerns about potential real-estate bubbles and the need for monitoring by analysts (see Figure 12).

Figure 12. Housing price index and common factor during the COVID-19 crisis



Note. The figure compares the evolution of the housing price index (HPI) and the estimated common factor during the COVID-19 crisis. It shows the sustained increase in housing prices despite periods of economic volatility, contrasting with the more fluctuating behavior of the common factor. This pattern suggests potential imbalances in the real estate market that may require close monitoring. Author's own calculations.

4.4. Transferability to other national contexts

Although the empirical application in this study focuses on the United States, the proposed mixed-frequency dynamic factor monitoring framework is, in principle, transferable to other national contexts, including emerging economies. However, such transferability requires specific statistical, institutional, and data-availability conditions. Statistically, the method assumes stable latent co-movement among macroeconomic indicators, with common factors capturing cyclical dynamics. In emerging economies characterized by structural breaks, heightened volatility, and limited data samples, factor stability may be compromised. As such, implementing additional robustness strategies (such as utilizing shorter rolling windows, adopting break-adjusted estimation methods, or incorporating time-varying parameters) becomes essential.

From an institutional and data standpoint, achieving effective implementation necessitates adherence to established standards of periodicity, timeliness, and comparability for key macroeconomic indicators such as inflation rates, labor market statistics, and interest rates. This must be supported by transparent release schedules and robust revision protocols. These considerations are especially critical in emerging settings, where statistical agencies may encounter inconsistencies in measurement methodologies or shifts in definitions.

Evidence from the Mexican literature suggests that cycle-oriented frameworks can be meaningfully implemented when adequate series are available and properly transformed. For instance, Román de la Sancha et al. (2019) document significant co-movement between stock market indices and economic cycles in the U.S.-Mexico setting, highlighting cross-country cyclical linkage channels that are relevant for monitoring applications. Likewise, Camacho Ardila et al. (2023) propose a coincident index for the Mexican banking sector using principal component methods, illustrating that factor-based monitoring tools can be adapted to emerging economies when data harmonization and indicator selection are carefully addressed.

Therefore, extending the proposed framework beyond the U.S. should be viewed as feasible but conditional: it requires sufficient data frequency and coverage, rigorous preprocessing (stationarity and seasonal adjustment), and institutional continuity in macroeconomic reporting. Under these conditions, the model can support real-time monitoring not only of national business cycles but also of sectoral financial cycles in emerging economies.

5. Conclusions

In conclusion, during the first analysis period, the Common Factor signaled a contraction in the U.S. economy beginning in early 2004. This was based on declining GDP, high inflation levels, rising interest rates, and sustained growth in housing values, all of which presaged the start of the Subprime crisis. On the other hand, the Common Factor’s recovery began about eight months before the officially declared end of the crisis, as defined by the NBER, relying on GDP recovery and near-zero interest rates. Additionally, the peak in the housing price index in April 2007 preceded the start of the crisis by eight months (as per the NBER definition). Throughout this entire first period, the labor market continued to feel the effects of the crisis.

During the second analysis period, all variables experienced significant effects. However, interest rates and inflation had the greatest impact due to the COVID-19 pandemic. Besides being directly affected by the health crisis, they were also heavily influenced by the conflict between Ukraine and Russia, reflected in the Common Factor's contraction. Furthermore, in this period, the Common Factor showed its capacity to predict the start of the recovery after the health crisis.

In closing, the performance of any single variable is not sufficient to determine U.S. business cycles. Also, each variable's behavior relative to the cycles was not uniform over time. For example, interest rates at times were in synchrony with the business cycle and the Common Factor, while at other times they were not. Moreover, some variables remain below their pre-pandemic levels. At the time of this research, we can conclude that the U.S. economic cycle is in a contraction phase, characterized by inflation that is under control but still above the target (3.25% versus 2%), interest rates that have not yet started to decline, and labor-force participation rates below those observed before the pandemic.

The model demonstrates that it can accurately represent how shocks—such as the Subprime crisis, the COVID-19 pandemic, and the Ukraine–Russia conflict—affect the economy. The MFD-FM can be considered efficient in adapting to economic changes and international policies.

6. Final Remarks

The originality of this study lies in its real-time application of the Mixed-Frequency Dynamic Factor Model to monitor U.S. business cycles using an extensive and carefully curated set of monthly and quarterly indicators. By integrating heterogeneous information within a unified framework that reacts immediately to newly released data, the model offers a more responsive and informative assessment of economic dynamics compared to traditional quarterly approaches. The full real-time implementation, relying solely on data available at each historical point, adds further methodological value by providing a realistic evaluation of the model's operational performance.

Despite its strengths, the study faces certain limitations that are inherent to real-time macroeconomic analysis. The model's performance depends on the availability and timeliness of monthly indicators, and revisions to key variables such as GDP can reshape the interpretation of past economic conditions. Nevertheless, the results demonstrate that mixed-frequency approaches substantially improve the identification of turning points relative to traditional frameworks, reinforcing their relevance for institutions engaged in economic surveillance, policymaking, and risk assessment.

The findings also suggest promising avenues for future research. Incorporating additional high-frequency indicators, such as weekly financial conditions or labor market metrics, may enhance the model's responsiveness to rapidly evolving economic environments. Exploring nonlinear or regime-switching structures could capture more complex cyclical behaviors, while applications to subnational economies or emerging markets may help validate the robustness of the methodology and reveal structural differences in business cycle transmission.

Overall, the study shows that the MFD-FM model provides timely and internally consistent measures of U.S. business cycle fluctuations, anticipating expansions and contractions earlier than quarterly methods. Its strong alignment with NBER recession dating highlights its practical relevance for real-time monitoring. By demonstrating the value of integrating monthly indicators into the assessment of cyclical dynamics, this research advances the scientific understanding of real-time macroeconomic analysis and contributes a robust framework for future developments in nowcasting and early-warning systems.

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Appendix A.

Ethical Considerations

It is important to note that ChatGPT (GPT-5, OpenAI) was used to reformulate certain sections of the text for clarity and to improve the style in academic English. The use of this tool was strictly aimed at rewriting and not for generating data, results, or conclusions. Additionally, the tool was employed with the aim of increasing the accessibility of the content and facilitating its understanding for a wider audience, helping the research work become more widely known. The author assumes full responsibility for the accuracy and coherence of the final content of the manuscript[3]. The AI tool was not used at any stage for data analysis or decision-making regarding the research outcomes.

[3] This use of AI tools complies with the guidelines set by the Committee on Publication Ethics (COPE) regarding authorship and ethical considerations in research. For more details, refer to the official statement at: https://publicationethics.org/guidance/cope-position/authorship-and-ai-tools.

Appendix B.

Descriptive Statistics and Stationarity Tests of U.S. Macroeconomic Time Series.
(Histograms, Q–Q Plots, Normality and Unit Root Tests)

This appendix summarizes the descriptive and stationarity analysis of the U.S. macroeconomic time series used in the model. It presents histograms, Q–Q plots, descriptive statistics of transformed variables, and results from normality (JB, K^2, Shapiro) and unit root (ADF, KPSS) tests. The objective is to verify the distributional assumptions and stationarity conditions required for consistent model estimation.

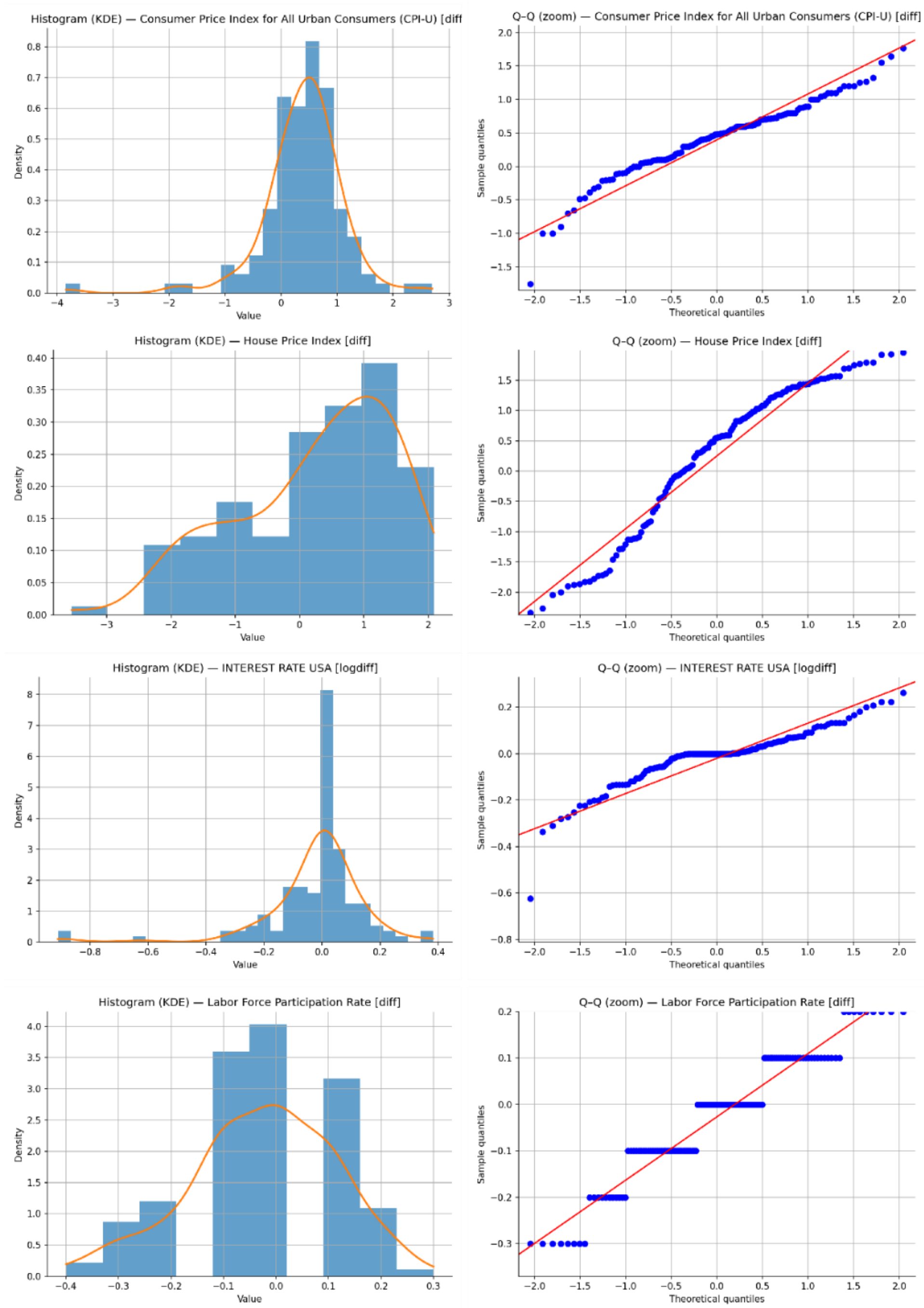
The variables considered are:

- Gross Domestic Product (GDP): Real quarterly output, used as the main reference for economic activity.
- Consumer Price Index (CPI): Monthly measure of inflation reflecting changes in the general price level.
- Interest Rates (IR): Short-term policy rate representing monetary conditions.
- Labor Force Participation Rate (LFPR): Monthly indicator of the proportion of the working-age population participating in the labor market.
- House Price Index (HPI): Monthly measure of residential property prices, reflecting trends in the housing market.

B.1. Graphical Analysis (Histograms and Q–Q Plots)

Figure B1 presents the histograms with kernel density estimates (KDE) and the corresponding quantile–quantile (Q–Q) plots of the transformed U.S. macroeconomic series used in the model: Consumer Price Index for All Urban Consumers (CPI-U), House Price Index (HPI), Interest Rate (IR), and Labor Force Participation Rate (LFPR), for the period 2000–2024. The left panels display the empirical distributions with smoothed kernel density curves, allowing for the examination of shape, asymmetry, and dispersion. The right panels show the Q–Q plots comparing the sample quantiles with those of a theoretical normal distribution.

Figure B1. Histograms (KDE) and Q–Q plots of transformed economic series (CPI-U, HPI, IR, and LFPR) in the United States, 2003–2013



Note. The figure presents histograms with kernel density estimates (KDE) and corresponding quantile–quantile (Q–Q) plots for the transformed macroeconomic series. The left panels show empirical distributions with density curves, while the right panels compare sample quantiles with a theoretical normal distribution to assess deviations from normality. Author's own calculations.

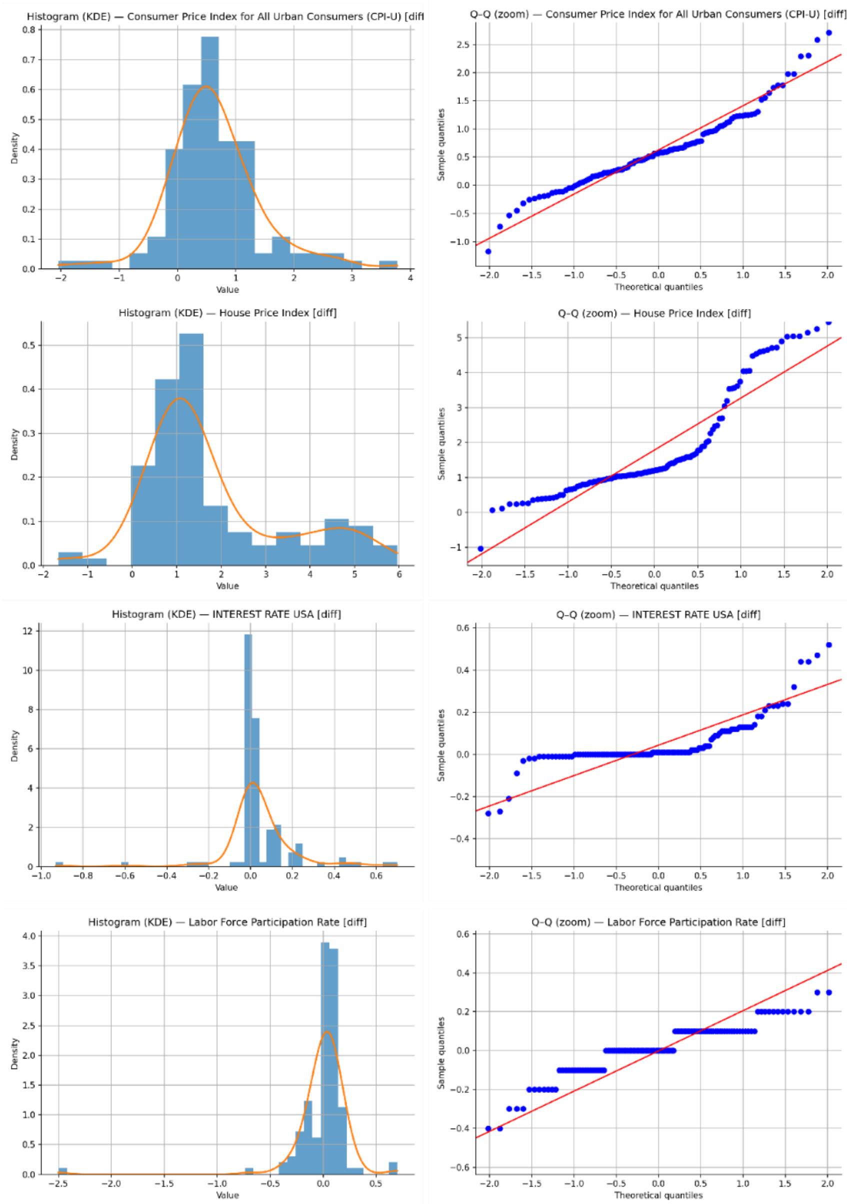
During the analyzed period, the series exhibit the following patterns:

- Gross Domestic Product (GDP): distribution centered around zero with a slightly flattened shape, indicating positive and negative fluctuations around a stable growth trend.
- Interest Rate (IR): pronounced tails and negative skewness, associated with near-zero interest rate episodes during the 2008 financial crisis.
- Consumer Price Index (CPI-U): negatively skewed with high peaks, reflecting temporary deflationary periods followed by price recovery.
- Labor Force Participation Rate (LFPR): approximately normal distribution with mild tails, suggesting persistent labor market shocks after 2008.
- House Price Index (HPI): displays a strong negative peak in 2008–2009 and a long left tail, capturing the sharp decline in housing prices during the real estate crash.

The Q–Q plots reveal pronounced *S-shaped* curves, indicating heavy tails and asymmetry in most series. In particular, Interest Rate and CPI-U show points below the reference line at higher quantiles and above it at lower ones, confirming negative skewness. The HPI exhibits the largest departure from normality, while the LFPR shows the best relative fit.

Overall, the visual evidence suggests that although the applied transformations mitigate non-normality, several series still display mild asymmetry and excess kurtosis—typical features of macroeconomic time series data.Figure B2 presents the histograms with kernel density estimates (KDE) and the corresponding quantile–quantile (Q–Q) plots of the transformed U.S. macroeconomic time series used in the model: *Consumer Price Index for All Urban Consumers (CPI-U)*, *House Price Index (HPI)*, *Interest Rate (IR)*, and *Labor Force Participation Rate (LFPR)*, for the period 2014–2024. The left panels show the empirical distributions of each transformed variable, along with their smoothed KDE curves, which provide insights into the shape, dispersion, and skewness of the data. The right panels display the corresponding Q–Q plots comparing the sample quantiles to those of a theoretical normal distribution.

Figure B2. *Histograms (KDE) and Q–Q plots of transformed economic series (CPI-U, HPI, IR, and LFPR) in the United States, 2014–2024*



Note. The figure presents histograms with kernel density estimates (KDE) and corresponding quantile–quantile (Q–Q) plots for the transformed macroeconomic series. The left panels display empirical distributions with density curves, while the right panels compare sample quantiles with a theoretical normal distribution to assess deviations from normality. Relative to the earlier period, most series exhibit distributions closer to normality, although mild asymmetry and heavy tails remain in some variables. Author's own calculations.

Overall, the histograms and Q–Q plots indicate that most transformed variables approximate a near-normal distribution, though with some degree of asymmetry and heavy tails — features that are common in macroeconomic datasets. Specifically:

- CPI-U: nearly symmetric distribution centered around zero, suggesting moderate inflation stability over the analyzed period.
- HPI: right-skewed distribution with long tails, consistent with pronounced housing price increases during expansionary phases.
- Interest Rate (IR): sharp peak near zero and slight left skewness, reflecting the prolonged period of low interest rates following the 2008 financial crisis.
- LFPR: concentrated around zero with a narrow spread, indicating limited short-term variation but potential structural changes in labor participation over time.

The Q–Q plots confirm mild deviations from normality, with *HPI* and *IR* showing the largest departures, while *CPI-U* and *LFPR* display a closer fit to the theoretical normal line. These graphical diagnostics complement the results of normality and unit root tests presented in the subsequent tables. Following the graphical analysis presented in Section B.1, this subsection reports the descriptive and econometric diagnostics that quantitatively assess the distributional properties and stationarity of the transformed series.

B.2. Descriptive Statistics (Transformed Series)

This subsection summarizes the results of the descriptive statistical analysis, normality tests, and stationarity diagnostics for five major U.S. macroeconomic variables: *Gross Domestic Product (GDP)*, *Interest Rate (IR)*, *Consumer Price Index for All Urban Consumers (CPI-U)*, *Labor Force Participation Rate (LFPR)*, and *House Price Index (HPI)*. The analysis covers two periods—2003–2013 and 2014–2024—and employs transformed series (*diff* or *logdiff*) selected to achieve optimal stationarity and comparability across indicators.

Descriptive Statistics of Transformed Series

Table B1. *Descriptive statistics of transformed macroeconomic series and interpretation (2003–2013 vs. 2014–2024)*

Variable	2003–2013	Interpretation	2014–2024	Interpretation
GDP USA	mean ≈ 0 skew ≈ 0 kurt ≈ 3	Stationary, symmetric	mean ≈ 0.01 mild skew +	Stable mild expansion
Interest Rate	skew – kurt > 10	Zero-rate collapse (2008)	Bimodal kurt ≈ 14	COVID zero-rate & 2022 hikes
CPI-U	mean ≈ 0.4 skew – kurt ≈ 12	Deflation & recovery	mean ≈ 0.6 skew + kurt ≈ 6	Inflation persistence
LFPR	Stable low variance	Gradual decline	skew – high kurtosis	COVID collapse & recovery

HPI	skew – kurt ≈ 2.6	Housing crash 2008	skew + kurt ≈ 3.3	Strong price growth

Note. The table summarizes descriptive statistics of transformed macroeconomic variables across two periods. Values are approximate and reported for comparative interpretation. Skew refers to skewness and kurt to kurtosis

After transformation, the series display distinct volatility and symmetry regimes:

- 2003–2013**:** High kurtosis (>10) and negative skewness, driven by the 2008 subprime crisis.
- 2014–2024**:** Moderate kurtosis (3–6) with positive skewness, associated with post-pandemic inflation.

GDP and LFPR remain centered around zero mean, confirming effective detrending. Both periods present high kurtosis (heavy tails) and pronounced asymmetry: negative during 2003–2013 (crisis phase) and positive during 2014–2024 (expansion and inflation period).

Normality Tests (p-values: JB, K^2, Shapiro)

Table B2. *Normality test results (p-values: Jarque–Bera, K^2, and Shapiro–Wilk) for transformed macroeconomic series*

Variable	2003–2013	Result	2014–2024	Result
GDP USA	<0.05	Non-normal	<0.05	Non-normal
Interest Rate	<0.05	Non-normal	<0.05	Non-normal
CPI-U	<0.05	Non-normal	<0.05	Non-normal
LFPR	≈0.05	Near-normal	<0.05	Non-normal
HPI	<0.05	Non-normal	<0.05	Non-normal

Note. Reported values correspond to p-values from Jarque–Bera (JB), D'Agostino's K^2, and Shapiro–Wilk tests. A p-value below 0.05 indicates rejection of the null hypothesis of normality.

Normality tests consistently reject the null hypothesis of normality for most variables, confirming heavy-tailed distributions and asymmetry across both subperiods—typical features of macroeconomic data.

Augmented Dickey–Fuller (ADF) Test (p-values)

Table B3. *Augmented Dickey–Fuller (ADF) unit root test results (p-values) for transformed macroeconomic series*

Variable	2003–2013 (p)	Interpretation	2014–2024 (p)	Interpretation
GDP USA	0.018	Stationary	0.016	Stationary
Interest Rate	0.005	Stationary	0.004	Stationary
CPI-U	0.003	Stationary	0.39	Non-stationary
LFPR	0.017	Stationary	0.012	Stationary
HPI	0.022	Marginally stationary	0.028	Weakly stationary

Note. Reported values correspond to p-values from the Augmented Dickey–Fuller (ADF) test. A p-value below 0.05 indicates rejection of the null hypothesis of a unit root (i.e., the series is stationary).

The ADF results confirm stationarity for most transformed series. The exception is CPI-U during 2014–2024, which exhibits non-stationarity, likely reflecting persistent inflation dynamics.

KPSS Test (p-values)

Table B4. *KPSS stationarity test results (p-values) for transformed macroeconomic series*

Variable	2003–2013 (p)	Interpretation	2014–2024 (p)	Interpretation
GDP USA	0.10	Stationary	0.10	Stationary
Interest Rate	0.10	Stationary	0.08	Stationary
CPI-U	0.10	Stationary	0.01	Trend non-stationary
LFPR	0.10	Stationary	0.07	Stationary
HPI	0.10	Stationary	0.02	Weak trend persistence

Note. Reported values correspond to p-values from the Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test. Unlike the Augmented Dickey–Fuller (ADF) test, the null hypothesis of the KPSS test assumes stationarity. A low p-value indicates rejection of stationarity, suggesting the presence of a unit root or trend component.

The KPSS test results are consistent with the ADF outcomes, indicating overall stationarity for most variables except CPI-U and HPI during 2014–2024, which show mild trend persistence.

Interpretation Summary

The combined evidence from descriptive statistics, normality tests, and unit root tests suggests that:

- Most transformed macroeconomic series behave as stationary processes, suitable for dynamic factor model estimation.
- CPI-U and HPI display limited non-stationarity in the later period, consistent with persistent inflation and post-pandemic asset price adjustments.
- The persistence of heavy tails (high kurtosis) and skewness reflects underlying economic shocks and recovery phases.

These findings validate the applied transformations and confirm that the dataset meets the statistical prerequisites for reliable model estimation in the main analysis.