Estimating the Macroeconomic Impact of Industrial Shocks: A Supply Chain Risk Analysis Using Conditional FAVAR Model

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Abstract

Recent global events such as the COVID-19 pandemic, semiconductor shortages, and port congestion have shown that supply chain disruptions can affect entire economies by constraining production, increasing costs, and delaying trade flows. Despite their importance, few studies have quantitatively examined how such disruptions influence macroeconomic conditions. This study estimates the impact of supply chain disruptions on key macroeconomic variables, including output, prices, employment, and financial indicators. Industrial production in the United States is used as a representative variable for supply-side disturbances because it reflects aggregate changes in manufacturing and logistics activity. A conditional Factor-Augmented Vector Autoregression (FAVAR) model estimated through Kalman filtering is applied to analyze how industrial shocks propagate through the U.S. economy. The framework is further employed as a supply chain risk analysis tool to simulate scenarios in which supply chain disruptions lead to 10% or 20% reductions in industrial activity and to evaluate their potential macroeconomic effects.

1 Introduction and motivation

Global supply chains and production networks and logistics systems play a critical role in shaping macroeconomic outcomes. In recent years, disruptions in manufacturing activity arising from supply shortages, energy constraints, or shifts in global demand have underscored the interdependence between supply chains, production networks, and aggregate economic performance. Understanding how a sudden change in industrial production propagates through the U.S. economy is not only a question for macroeconomists but also for supply chain engineers and financial analysts concerned with risk management, resilience, and systemic exposures.

Traditional supply chain models often focus on firm-level or industry-level optimization under relatively stable external conditions. Yet large supply shocks are inherently macro in nature: they alter relative prices, shift resource allocation across sectors, and interact with monetary and financial conditions. Macroeconomic econometric tools, such as Factor-Augmented Vector Autoregressions (FAVARs), provide a complementary perspective by embedding production and supply chain indicators within a broader system of interrelated macro variables. This approach allows researchers to trace both the direct and indirect channels through which real-supply shocks influence output, employment, prices, and financial variables.

Our motivation in applying FAVAR methods to supply chain questions is twofold. First, macroeconomic factor models exploit information from a very large number of time series to recover a small set of latent common components, thereby summarizing the "state of the economy" . This dimension reduction is essential when the goal is to study trade shocks that are stongly coorelated with other macroeconomic forces. Second, the VAR framework, once augmented with these latent factors, yields impulse-response functions (IRFs) and forecast error variance decompositions (FEVDs) that provide an interpretable mapping from a trade shock to subsequent macroeconomic dynamics.

For supply chain engineering and finance, such tools are valuable because they quantify spillover effects that are not easily captured by micro-level models. For instance, an unexpected contraction in industrial production may constrain input availability for downstream manufacturers, raise production costs, or trigger cascading adjustments across logistics and credit markets. By embedding industrial production within a factor-augmented system, it becomes possible to evaluate these propagation channels and quantify how real-supply disturbances diffuse through the broader economy.

In the first part of this study, we will be focusing on the canonical FAVAR approach and its two-step principal components estimator were developed in the monetary policy literature by Bernanke et al. (2005). The motivation in using a Factor Augmented Model in stead of a classic Vector Auto Regression relies in the "curse of dimensionality". Unrestricted VAR suffer from a rapid proliferation of parameters as the number of observables grows (see Sims (1980). Therefore, it is natural to reduce multiple correlated variables into one (or more) explicit factors, at the cost of losing information through Factor Analysis. In parallel, the dynamic factor model (DFM) literature (e.g., Stock and Watson, 2002; Bai and Ng, 2002) provides theoretical foundations for estimation and factor selection. More recently, conditional forecasting in large systems, initially introduced by Clarida and Coyle (1984) and that has been advanced by Banbura et al. (2015), which detail Kalman filtering and smoothing techniques that naturally extend to FAVAR settings. Combining these features has never been done before and will be done in the second part of this study. By doing so, our paper aims to bridge macroeconometrics and supply chain analysis, offering both a methodological contribution and an applied investigation of trade shocks. The paper proposes a methodology for conditional forecasting by means of Kalman filtering/smoothing to a FAVAR model.

2 Outline

We proceed as follows. Section 2 gives a quick historical overview on the last two major crisis in the United States and their respective impact on Supply Chains. Section 4 sets up the FAVAR model, notation and estimation (data treatment, PCA algebra, factor normalization). Section 5 details IRF and FEVD formulae and inference. Section 6 develops the state-space representation, Kalman filter and smoother, and conditional forecasting. The last part focuses on a case study.

3 Historical Perspective

Over the past three decades, the U.S. industrial sector has experienced several major disruptions, coincidental with periods of recession and crisis, that have exposed vulnerabilities in global supply chains. Two episodes are particularly illustrative: the 2008–2009 Global Financial Crisis, and the 2020 COVID-19 pandemic.

1. The Global Financial Crisis (2008–2009) led to a severe contraction in global demand, with U.S. industrial production (INDPRO Index) falling by nearly 15% between mid-2008 and early 2009. Supply chains were disrupted not by physical constraints but by a collapse in credit markets and demand. Firms sharply curtailed inventories ("bullwhip effect") and idled capacity, as explained by Mefford (2009). The crisis highlighted the dependence of industrial and logistics systems on financial stress.

2. The COVID-19 Pandemic (2020–2022) The COVID-19 shock differed markedly from previous crises in that it was rooted in both supply and demand constraints. Lockdowns and mobility restrictions led to sudden halts in production, labor shortages, and logistics bottlenecks. The U.S. industrial production index declined by over 16% between February and April 2020. Unlike the 2008 crisis, recovery was rapid but uneven, complicated by semiconductor shortages, port congestion, and volatile demand for durable goods. Firms faced both excess inventories in some sectors and critical shortages in others, exposing the fragility of just-in-time supply models, as highlighted in Ramani et al. (2022). This episode prompted a renewed interest in supply chain resilience and diversification.

Across these episodes, industrial downturns propagated through multiple channels: credit tightening, input scarcity, logistics delays, and inventory imbalances. These shocks highlight the nonlinear interplay between industrial production, supply chain networks, and aggregate economic performance that the following model will try to explain.

4 Model setup: static factor model + VAR (FAVAR)

In this section we dive into the specifics and mathematical formulation of the FAVAR model. Let $\mathbf{X}_t \in \mathbb{R}^N$ be a (column) vector of the large panel of macroeconomic observables at time t. Partition the variables into

$$\mathbf{Y}_t \in \mathbb{R}^m \quad \text{(small set of target observables; here the tariffs rates exclusively)}$$

and the remaining $\mathbf{X}_t$ (the large informational set). Therefore, Y_t is set to be dimension $(K, 1)$ with $K = 1$ in this specific use case. Theoretically, K can be any dimension, but the more dimensions, the harder it becomes to explain the structural shocks in the VAR. Building on Boivin and Ng (2006), we decide to set N = 100 macro variables, as more will not necessarily increase the explained variance of the dataset when estimating the Dynamic Factor Model.
Each series are transformed to ensure stationarity: logarithms and differences / log-differences (e.g., $\Delta \ln x_t$) for levels that grow, differences for indices. Stationnarity tests are computed (ADF / KPSS) for additional verification.
The series then undergo a standardization process: $\tilde{x}_{i,t} = (x_{i,t} - \bar{x}_i)/s_i$ where $\bar{x}_i$ is the sample mean and s_i the sample standard deviation.

4.1 Static factor representation and estimation

Before estimating the parameters for the VAR, we implement a method of dimensionality reduction Assuming a static factor structure and following Bernanke et al. (2005) methodology:

$$\mathbf{X}_t = \Lambda^f \mathbf{F}_t + \Lambda^o \mathbf{Y}_t + \mathbf{e}_t, \qquad t = 1, \dots, T, \tag{1}$$

where

- $\mathbf{F}_t \in \mathbb{R}^r$ is the vector of r latent common factors. They are the unobserved factors driving the economy. The objective in the next part will be to determin these latent factors.
- $\Lambda^f \in \mathbb{R}^{N \times r}$ and $\Lambda^o \in \mathbb{R}^{m \times r}$ are factor loading matrices,
- $\mathbf{e}_t \in \mathbb{R}^N$ is the idiosyncratic term with $\mathrm{E}(e_t) = 0$ and $\Sigma_e \approx \mathbb{I}_{n,n}$.

T is set to be over 300 observations starting in January 2000 until most recent updates from the Federal Reserve (August 2025). r is set to be the number of principal components for this study. The determination for this number can be estimated using AIC/BIC, although for simplicity, we decided to keep the same numbers of factors as in Bernanke et al. (2005).

4.2 Principal components estimator in the FAVAR framework

Following Bernanke et al. (2005) and the replication approach of Duarte (2020), the factor extraction differs from the pure DFM of Stock and Watson (2002) in that the panel $\mathbf{X}_t$ is decomposed

into a part explained by observables $\mathbf{Y}_t$ and a residual part used for factor estimation. This part is necessary to remove the influence of the observed variables from the informational panel, ensuring that the estimated factors capture only the common variation not already explained by the observables.
Factor estimation for equation 1 can be done in the following steps:

1. Partialling out observables: Each standardized series in $\mathbf{X}_t$ is regressed on $\mathbf{Y}_t$, yielding fitted loadings $\widehat{\Lambda}^o$ and residuals
$$\mathbf{X}_t^{\perp} = \mathbf{X}_t - \widehat{\Lambda}^o \mathbf{Y}_t.$$
Stacking over $t = 1, \ldots, T$ gives the residual matrix $\mathbf{X}^{\perp} \in \mathbb{R}^{T \times N}$.

2. Principal components on residuals: The latent factors are estimated by solving
$$\min_{\mathbf{F}, \Lambda^f} \frac{1}{NT} \sum_{t=1}^{T} \left\| \mathbf{X}_t^{\perp} - \Lambda^f \mathbf{F}_t \right\|^2,$$
subject to the normalization
$$\frac{1}{T} \sum_{t=1}^{T} \mathbf{F}_t \mathbf{F}_t' = I_r.$$
The solution is given by principal components of $\mathbf{X}^{\perp}$. The reaminder of the computations follows the same methodology as Stock and Watson (2002).

3. Estimation of the loadings for the latent factors: Given $\widehat{\mathbf{F}}$, the factor loadings are obtained as
$$\widehat{\Lambda}^f = \frac{1}{T} (\mathbf{X}^{\perp})' \widehat{\mathbf{F}}.$$

4.3 Latent Factor Extraction and Macroeconomic Interpretation

To capture the common dynamics underlying a large panel of macroeconomic and financial variables, we estimate a three-factor model using principal component analysis (PCA) applied to a standardized dataset comprising real, nominal, and financial indicators. The data are first transformed according to their respective stationary requirements, using first differences or log-differences as specified in the variable description sheet. After transformation and standardization, we extract the first three principal components, denoted by $\hat{F}_1$, $\hat{F}_2$, and $\hat{F}_3$, which together explain the majority of common variation across the dataset.

Each latent factor is subsequently "cleaned" by removing the contemporaneous effect of the unemployment gap proxy (`INDPRO`) through an auxiliary regression: $\hat{C} = F_{\text{slow}}\beta + \gamma \texttt{INDPRO} + \varepsilon$, where F_{slow} denotes the first three principal components extracted from a subset of "slow-moving" variables. The residual component, $\hat{F} = \hat{C} - \gamma \texttt{INDPRO}$, represents the set of orthogonalized latent factors capturing distinct macroeconomic sources of co-movement.

4.3.1 Visual Representation.

Figure 16 illustrates the cumulative behavior of the three estimated factors alongside representative macroeconomic series used as reference benchmarks. The first latent factor is plotted against the Producer Price Index (PPIACO), the second against the Durable Goods Production Index (DAUPSA), and the third against retail sales (RETAILIMSA). These visual comparisons aid in identifying the economic nature of each underlying factor.

4.3.2 Economic Interpretation.

The table 5 reports the ten variables most strongly correlated with each latent factor. These correlations serve as an empirical guide for the macroeconomic interpretation of the latent dimensions. The first factor ($\hat{F}_1$) is strongly associated with broad price measures, monetary aggregates, and industrial indicators, implying that it captures the *inflation and cost-pressure* component of the economy. Negative co-movements with inflation proxies (such as PPI and CPI) suggest that lower values of $\hat{F}_1$ coincide with inflationary episodes and energy price shocks.

The second factor ($\hat{F}_2$) correlates positively with loan and credit growth variables, energy-related inputs, and producer prices, indicating a *credit and domestic demand* dimension. This factor reflects the cyclical behavior of credit markets and demand-driven pressures that accompany expansions or contractions in investment and consumption activity.

The third factor ($\hat{F}_3$) is dominated by correlations with monetary aggregates (M1, M2, M1REAL) and interest-rate proxies, revealing a *monetary liquidity and policy stance* interpretation. Periods of high values in $\hat{F}_3$ correspond to monetary accommodation or liquidity expansion, while low values suggest tightening conditions.

Overall, the factor structure aligns well with the following macroeconomic interpretation: $\hat{F}_1$: Inflation and cost-push factor, $\hat{F}_2$: Credit and demand cycle, $\hat{F}_3$: Monetary and liquidity policy.

4.3.3 How the latent factors explain the data ?

Given the estimated measurement relation $\mathbf{X}_t = \Lambda^f \hat{\mathbf{F}}_t + \Lambda^o \mathbf{Y}_t + \mathbf{e}_t$, we evaluate in-sample fit by comparing each observable $X_{i,t}$ with its fitted value $\widehat{X}_{i,t} = \hat{\lambda}_i^{f\prime} \hat{\mathbf{F}}_t + \hat{\lambda}_i^{o\prime} \mathbf{Y}_t$.

The resulting fits summarize how much of each series is explained by common forces versus idiosyncratic movements.

4.3.4 Example: Two series largely explained by common factors.

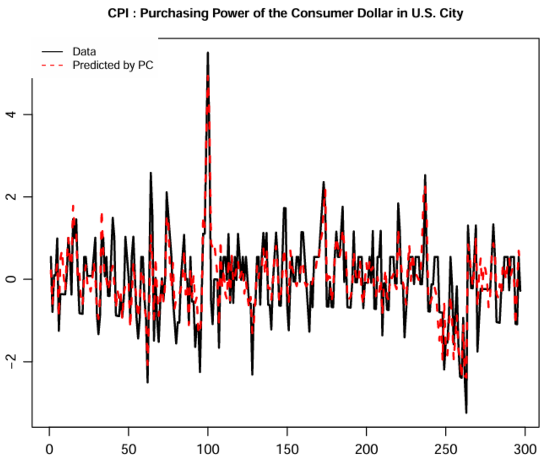
- CPI: purchasing power of the dollar is tracked closely by the factors. This is expected: the purchasing-power series responds to pervasive price pressures (pass-through of import costs, sector-wide markups), which the estimated factors absorb from many price and activity indicators. Additionnaly, a lot of CPIs where used for this study. Therefore, the large co-linearity between most of them influence the estimation of the latent factors by principal component.
- Retail inventories are also well explained. In both cases, the cross-sectional signals embedded in $\mathbf{X}_t$ allow $\hat{\mathbf{F}}_t$ to pick up the dominant low-frequency and cyclical components that drive these aggregates.

4.3.5 One series the model fits poorly.

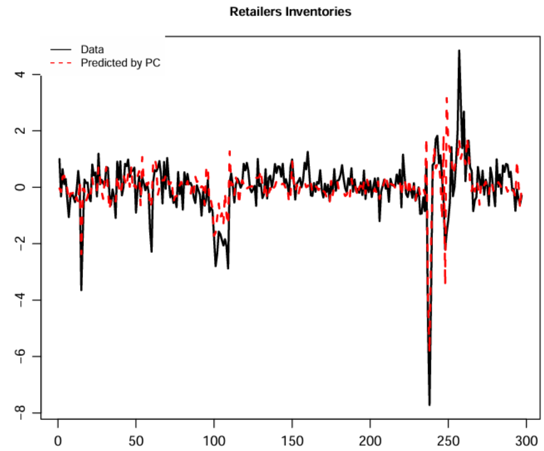
Housing prices tend to move slowly and are influenced by local conditions such as supply constraints, land availability, and financing costs. Those are elements that the national factors cannot easily capture. Because home prices are highly persistent and less sensitive to production shocks, their reaction is muted. Furthermore, this variable is one of the only ones representing home prices in the entire dataset, making it difficult for $\hat{\mathbf{F}}_t$ to pick up the trends.

4.3.6 A benchmark series fit by construction.

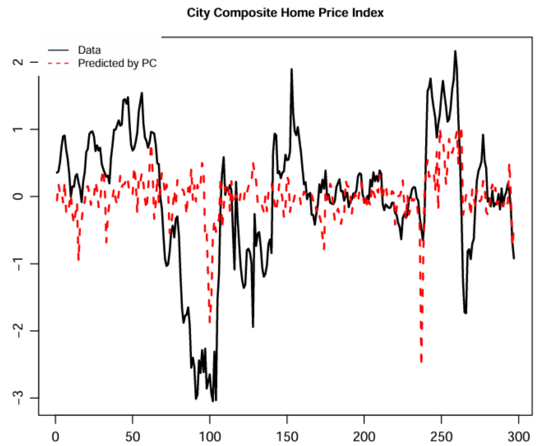
Industrial Production Index (INDPRO) is matched exactly, as the variable is included among the observables in $\mathbf{Y}_t$ and enters the measurement equation by hypothesis of the FAVAR. This confirms that the mapping from observables to the fitted panel is working as intended.



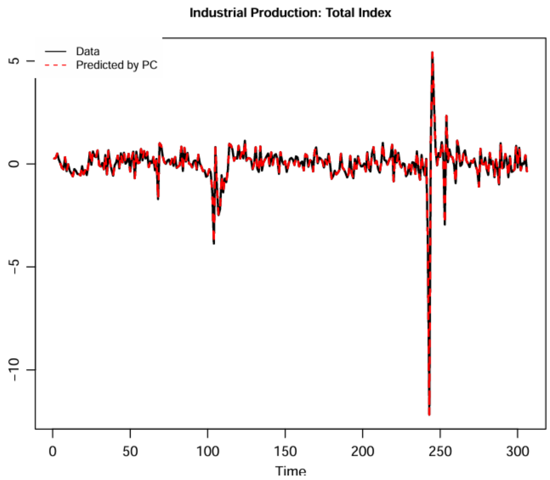
(a) CPI: Purchasing Power of the Dollar (good fit)



(b) Retail Inventories (good fit)



(c) U.S. City Composite Home Price Index (weak fit)



(d) Industrial Production Index (one-to-one)

Figure 1: Observed series (black) and fitted values from the measurement equation using latent factors and the tariff observable (dotted red).

Where the factors perform strongly (CPI purchasing power, retail inventories), the series are primarily driven by economy-wide forces that the panel shares. It will be shown later on that these are also the variables that perform the best when forecasting the FAVAR model. Where the fit is weak (home prices), dominant drivers are local or asset-market specific and only weakly connected to national comovement.

4.4 Factor dynamics and the augmented VAR (FAVAR)

Once the latent factors are determined and the loadings are computed, we form the stacked vector:

$$\mathbf{z}_t = \begin{pmatrix} \hat{\mathbf{F}}_t \\ \mathbf{Y}_t \end{pmatrix} \in \mathbb{R}^{r+m}$$

and model $\mathbf{z}_t$ by a VAR(p), with p the number of lags in the autoregression process:

$$\mathbf{z}_t = \sum_{l=1}^{p} A_l \cdot \mathbf{z}_{t-l} + \mathbf{v}_t \qquad \mathbb{E}[\mathbf{v}_t \mathbf{v}_t'] = \Sigma_v, \tag{2}$$

with $A_l \in \mathbb{R}^{(r+m)\times(r+m)}$. This is the standard FAVAR object of interest: $\mathbf{F}_t$ summarize the information in the large panel, and together with the target observables $\mathbf{Y}_t$ we aim to study how the latent factors might evolve conditional to shocks or an expected future path on the observable. Parameters for the VAR(p) in equation (2) can be estimated by OLS to obtain $\widehat{A}_1, \ldots, \widehat{A}_p$ and residual covariance $\widehat{\Sigma}_\varepsilon$.

5 Impulse Response Function (IRF) and FEVD

The primary purpose of estimating a FAVAR is to study the dynamic propagation of shocks in a large-dimensional economic system while keeping the number of estimated parameters manageable. Impulse response functions (IRFs) and forecast error variance decompositions (FEVDs) are the two key tools for this purpose. They allow us to quantify (i) the dynamic effect of a one-time structural innovation (IRFs), and (ii) the relative importance of different shocks in explaining the variability of each variable at different horizons (FEVDs). They are the standard tools for dynamic analysis in VARs (Lütkepohl (1990)). We apply them in the FAVAR setting to study the effect of an industrial production shock.

By imposing an exogenous decrease in Industrial Production, the IRFs trace out the dynamic responses of latent factors F_t and observables Y_t at $T+1, T+2, ..T+h$ (h the forecast horizon). These responses can be mapped back to actual macroeconomic indicators using equation 1. The FEVDs quantify the proportion of variability in each variable that can be attributed to the industrial production shock, as opposed to other sources of disturbance.

5.1 Cholesky Decomposition Assumption and IRF

An important identification step is to transform the correlated reduced-form residuals $\boldsymbol{\varepsilon}_t$ from the VAR into orthogonal structural shocks $\mathbf{u}_t$. Since $\mathrm{Cov}(\mathbf{v}_t) = \Sigma_v \neq I$, we apply a Cholesky decomposition:

$$\Sigma_\varepsilon = BB', \qquad \boldsymbol{\varepsilon}_t = B\mathbf{u}_t, \quad \mathbf{u}_t \sim \mathcal{N}(0, I),$$

where B is a lower-triangular matrix.

The ordering of variables in $\mathbf{z}_t = (F_1, F_2, F_3, Y_t)'$ determines the identification scheme. The latent factors are allowed to affect Y_t contemporaneously, but Y_t does not affect the factors within the same period. This reflects the assumption that shocks to industrial production are exogenous within the preiod and can contemporaneously influence the broader macroeconomic factors, but not the reverse.

This recursive structure identifies the structural tariff shock $u_{Y,t}$, which is then used to compute the impulse responses of both latent factors and observables.

5.2 Forecast error variance decomposition (FEVD)

The contribution of structural shock k to the h-step ahead forecast error variance of variable i is

$$\mathrm{FEVD}_{i,k}(h) \;=\; \frac{\sum_{s=0}^{h-1}\left(e_i'\Psi_s B e_k\right)^2}{e_i'\left(\sum_{s=0}^{h-1}\Psi_s\Sigma_\varepsilon\Psi_s'\right)e_i}. \tag{3}$$

FEVDs quantify the relative importance of each shock in explaining the variability of a variable over different horizons. In this paper, this decomposition answers the question: *when a disruption occurs in production or logistics representing a real supply chain shock how much of the forecast uncertainty in key U.S. macroeconomic indicators such as employment, inflation, and financial conditions can be traced back to that disturbance?*. This makes FEVD a natural complement to IRFs: while IRFs trace the path of adjustment to one shock, FEVDs provide a sense of how "structurally important" that shock is in the overall system.

5.3 Dynamic propagation of an industrial production shock

This section examines how a negative shock to industrial production propagates through the broader U.S. economy. Figure 2 to 6 summarizes the estimated impulse responses from the FAVAR model. Together, these results trace how a real production disturbance transmits across energy markets, supply chains, and macroeconomic aggregates such as employment, prices, and financial conditions.

5.3.1 Initial Supply Chain Adjustment

A negative industrial production shock first transmits upstream through the logistics and inventory channels that support goods movement. The freight transportation index falls sharply, indicating an immediate contraction in the shipment of intermediate and finished goods. This decline reflects the rapid response of distribution networks to reduced factory output and weaker demand for freight services.

Retail and business inventories exhibit a brief, moderate rise in the initial phase, as firms temporarily rely on accumulated stock to maintain deliveries despite lower production levels. However, this adjustment is short-lived. As manufacturing activity continues to contract and replenishment orders slow, inventories begin to decline rapidly. The resulting drawdown reflects both the depletion of existing stock and the postponement of new restocking cycles.

This sequence a near-instant decline in freight volumes, a transitory inventory rise, and a subsequent sharp drawdown illustrates the forward position of logistics and inventories in the industrial transmission mechanism. These variables typically respond within one to two quarters of the shock, serving as early indicators of tightening supply conditions across the production network.

5.3.2 Effects on Manufacturing and Production Activity

As the shock propagates, it directly affects the broader goods-producing sector. Industrial production declines persistently, driven by lower input utilization, higher unit costs, and weaker downstream demand. Manufacturers facing excess capacity and elevated uncertainty reduce operating hours and delay new capital investments, reinforcing the contraction in output.

The auto industry exhibits one of the strongest responses to the industrial production shock. Domestic auto production falls markedly, consistent with its dependence on complex supplier networks and its sensitivity to cyclical fluctuations in industrial demand. In contrast, vehicle sales decline less severely and begin to stabilize after several quarters, as households gradually resume postponed purchases of durable goods once economic conditions normalize.

Overall, these dynamics highlight the central role of industrial production as the anchor of the real-economy adjustment process. The decline in manufacturing output triggers immediate reductions in freight activity and inventory replenishment, while indirectly weakening demand for durables and transportation services. The pattern mirrors classic production-cycle dynamics, in which cost-driven contractions in manufacturing propagate gradually to consumption and prices.

5.3.3 Aggregate Demand and Price Dynamics

Following the decline in industrial output, aggregate demand weakens with a short lag. The personal consumption expenditures (PCE) index falls moderately and remains below baseline for several quarters, reflecting income effects from slower hiring in manufacturing and transportation as well as delayed durable purchases. Service-sector spending adjusts more gradually but contributes to the persistent softness in overall consumption.

On the price side, the consumer price index (CPI) rises with a delay of roughly three to four quarters. Initially, firms absorb cost pressures through lower margins to support sales volumes amid weak demand. As conditions stabilize and pricing contracts adjust, cost pass-through becomes more pronounced, leading to a mild and lagged increase in consumer prices. The coexistence of subdued output and gradually rising prices is consistent with a temporary supply-side constraint rather than a demand-led inflationary episode.

5.4 Variance decomposition and factor contributions

Table 6 ranks all observables by their R^2 from the factor regressions. The top of the table is dominated by real activity and price variables such as industrial production, consumption, employment, and CPI measures. This indicates that the estimated factors capture most of their comovement. At the bottom of the ranking, housing, credit, and uncertainty indicators exhibit low R^2, suggesting that they are driven by idiosyncratic or structural components outside the factor space. Each observable X_i is modeled as a linear combination of the common factors and the industrial production policy factor:

$$X_i = \lambda_{i1}F_{1t} + \lambda_{i2}F_{2t} + \lambda_{i3}F_{3t} + \lambda_{iY}Y_t + e_{it}.$$

With $\lambda_{i,j} \in (\Lambda^f, \Lambda^o)$ After normalizing all factors to have unit variance, the variance decomposition for variable i is:

$$\mathrm{Var}(X_i) = \lambda_{i1}^2 + \lambda_{i2}^2 + \lambda_{i3}^2 + \lambda_{iY}^2 + \sigma_{e_i}^2.$$

The share of variance explained by the industrial production factor is then defined as:

$$\text{Contribution}_{i,Y} = \frac{\lambda_{iY}^2}{\lambda_{i1}^2 + \lambda_{i2}^2 + \lambda_{i3}^2 + \lambda_{iY}^2 + \sigma_{e_i}^2}.$$

Table 1 presents variables with an R_i^2 greater than 0.50, indicating that the model explains more than half of their observed variance and thus provides meaningful explanatory power. We then cluster the variables based on their economic interpretation to analyze how different sectors respond to production shocks. Manufacturing Prices include various producer price indices (PPIs) reflecting upstream cost dynamics in the manufacturing sector. Energy and Commodity Prices cover global and domestic indicators such as crude oil, Brent, and gasoline prices which respond sensitively to changes in industrial production through adjustments in energy demand and market expectations. Inventories and Orders include retailers' inventories and new motor-vehicle orders, which reflect short-term adjustments in production planning and stock management following changes in industrial activity. Consumption and Prices encompass household demand and inflation indicators—such as Personal Consumption Expenditures (PCE) and the Consumer Price Index (CPI) that respond to shifts in production and income levels. Finally, Employment and Transportation Activity comprises measures of labor, logistics, and mobility—such as employment in transportation and warehousing and vehicle miles traveled capturing how real sector and transportation dynamics adjust to fluctuations in industrial output.

Variables	**Contribution**	R^2
(1) Manufacturing Prices		
PPI: All Commodities	6%	0.845
PPI: Industrial Commodities	6%	0.821
PPI Total Manufacturing Industries	6%	0.825
PPI : Crude Petroleum (Domestic Production)	6%	0.707
(2) Energy and Commodity Prices		
Global Price of WTI Crude ($/barrel)	8%	0.767
Crude Oil Prices (WTI) ($/gal)	7%	0.770
Crude Oil Prices: Brent - Europe ($/bar)	7%	0.764
Global Price of Brent Crude ($/Barrel)	7%	0.711
CPI : Energy in the US	5%	0.704
US Diesel Sales Price ($/gal)	5%	0.691
US Regular Gas Price ($/gal)	5%	0.697
(3) Inventories and Orders		
Retailers Inventories (B$)	6%	0.543
Total Business Inventories (M$)	6%	0.534
New Orders: Motor Vehicles and Parts (M$)	6%	0.672
(4) Consumption and Prices		
PCE: Durable Goods (B$)	6%	0.626
Personal Consumption Expenditures (B$)	5%	0.858
Personal Consumption Expenditures: Chain-type Price Index	5%	0.746
Personal Consumption Expenditures: Services (B$)	4%	0.802
CPI for All Urban Consumers	5%	0.767
Consumer Price Index: Total for United States	5%	0.767
CPI : Purchasing Power of the Consumer Dollar in U.S. City Average	5%	0.679
(5) Employment and Transportation Activity		
All Employees, Transportation and Warehousing (000s)	5%	0.635
All Employees, Retail Trade (000s)	5%	0.773
All Employees, Truck Transportation (000s)	5%	0.508
All Employees, Financial Activities (000s)	3%	0.627
Domestic Auto Production (000s)	4%	0.702
Vehicle Miles Traveled (MMiles)	4%	0.784

Table 1: High-R^2 Variables Grouped by Economic Category

5.5 Impulse Responses of Economic Categories to Industrial Production Shock

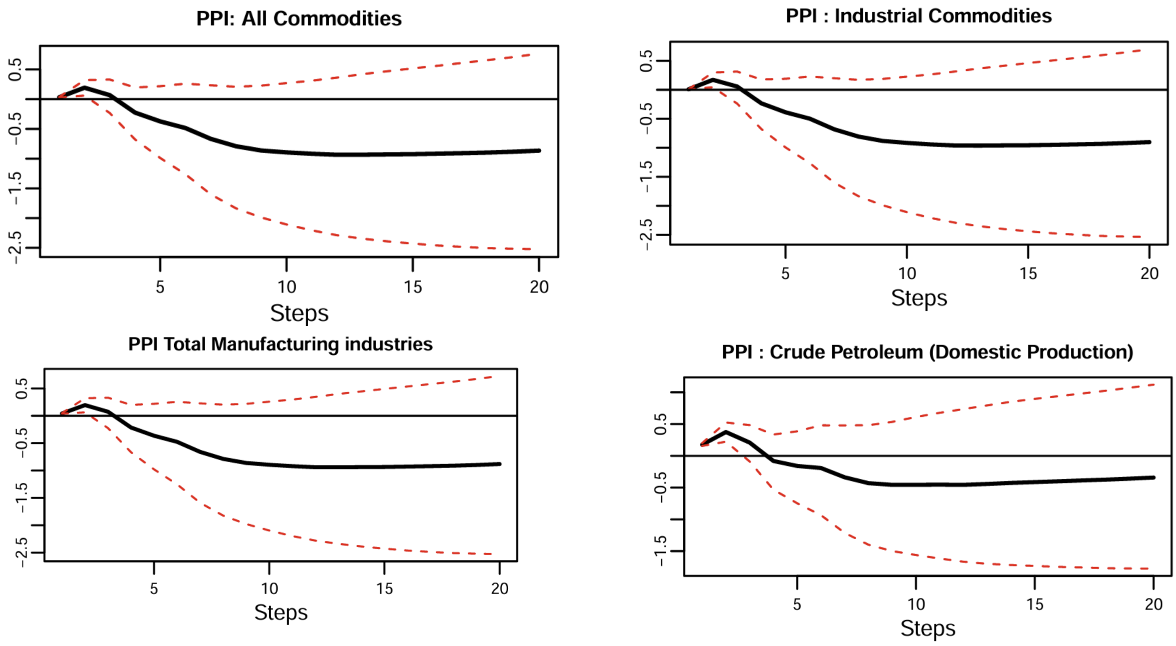


Figure 2: Group (1): Manufacturing Prices — IRFs to a negative industrial production shock.

In response to a negative industrial production shock, macroeconomic variables related to manufacturing prices such as the producer price indices (PPI) for all commodities, industrial commodities, and manufacturing industries tend to decline on average. Most responses remain below zero within the confidence bands, suggesting that lower industrial output generally places downward pressure on manufacturing prices through weaker demand for intermediate and final goods. The response is moderately persistent, indicating that the contraction in production is usually associated with reduced pricing power in the manufacturing sector over time.

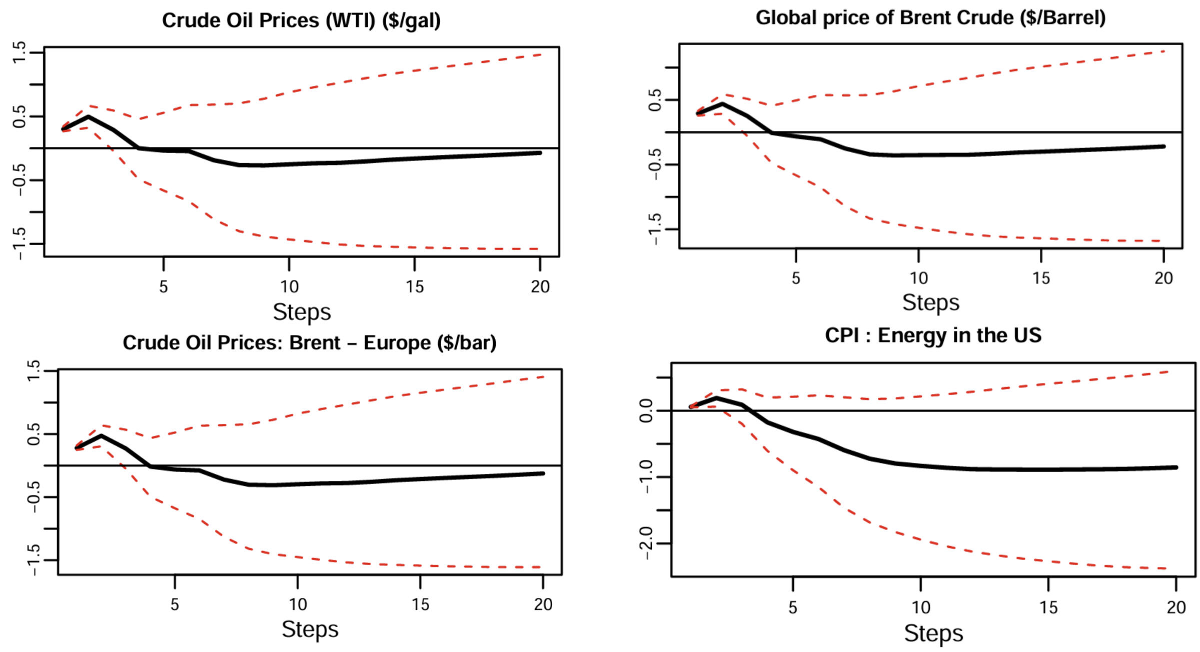


Figure 3: Group (2): Energy and Commodity Prices — IRFs to a negative industrial production shock.

Macroeconomic variables related to energy and commodity prices including crude oil, Brent, and gasoline prices also tend to decline following a negative industrial production shock. The average responses indicate that weaker industrial activity reduces energy demand and commodity consumption. This effect suggests that lower production levels are often linked to downward adjustments in global energy markets.

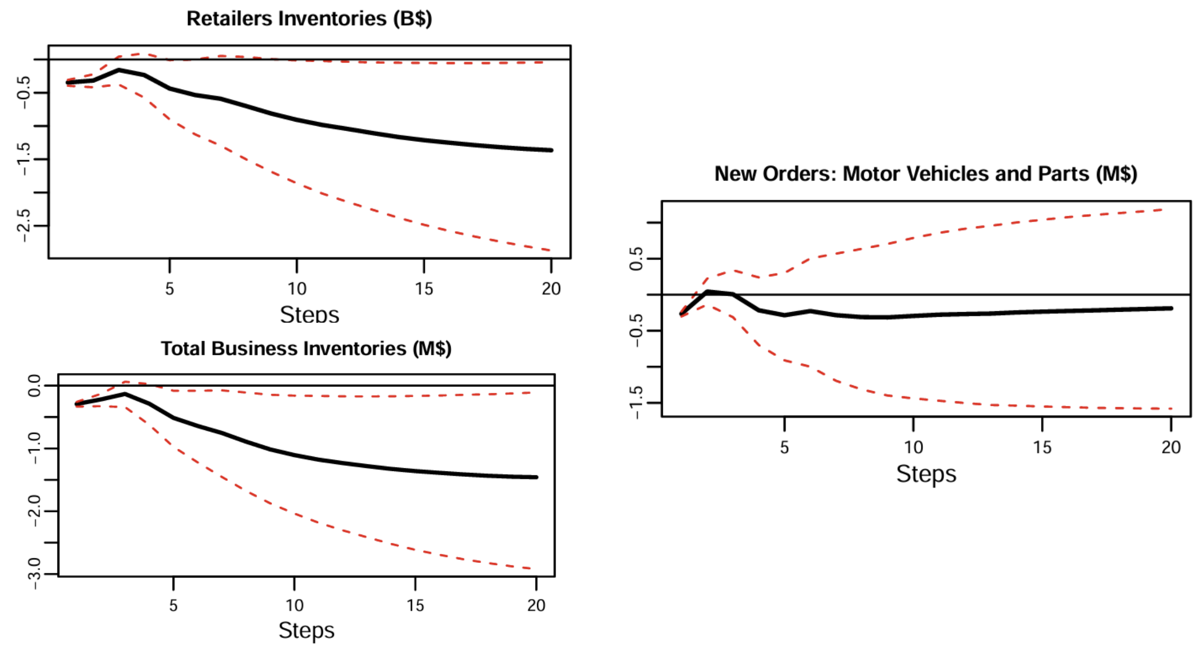


Figure 4: Group (3): Inventories and Orders — IRFs to a negative industrial production shock.

Variables capturing inventories and orders such as retailers' inventories and new motor vehicle orders tend to decrease after a negative industrial production shock. These declines reflect firms' short term adjustments in production planning and stock management as they align inventory levels with weaker sales and demand expectations. The responses show that businesses reduce new orders and inventory accumulation when production activity slows.

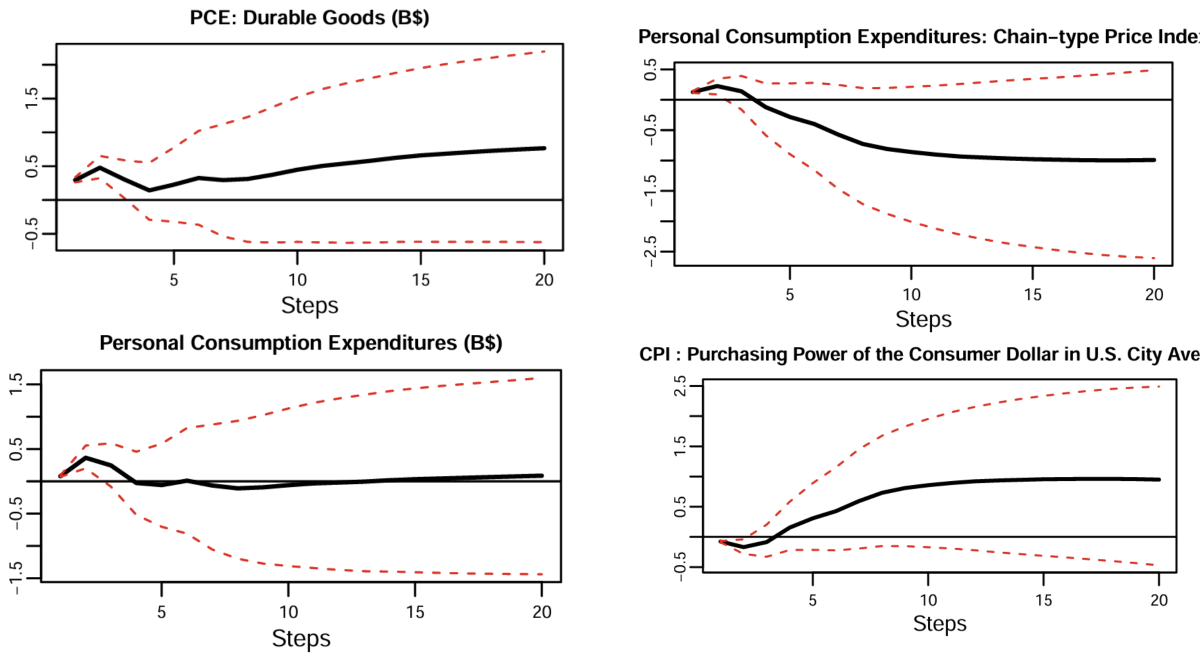


Figure 5: Group (4): Consumption and Prices — IRFs to a negative industrial production shock.

Macroeconomic variables related to consumption and prices such as personal consumption expenditures (PCE), PCE durable goods, and the consumer price index (CPI) show mixed responses to a negative industrial production shock. PCE durable goods tend to increase slightly, suggesting that consumers may shift toward long-lasting goods when prices or financing conditions become favorable after a slowdown. In contrast, the PCE price index and CPI tend to decline, indicating mild disinflation and a rise in the purchasing power of the consumer dollar. Overall, the responses imply that weaker industrial activity leads to softer price dynamics and moderate adjustments in household spending patterns. However, these mixed responses arise because most variables in this group are slow-moving macroeconomic indicators that adjust at different paces to production shocks. As a result, their impulse responses reflect gradual and sometimes heterogeneous adjustments rather than immediate short-term reactions, which is consistent with the nature of slow variables in the model.

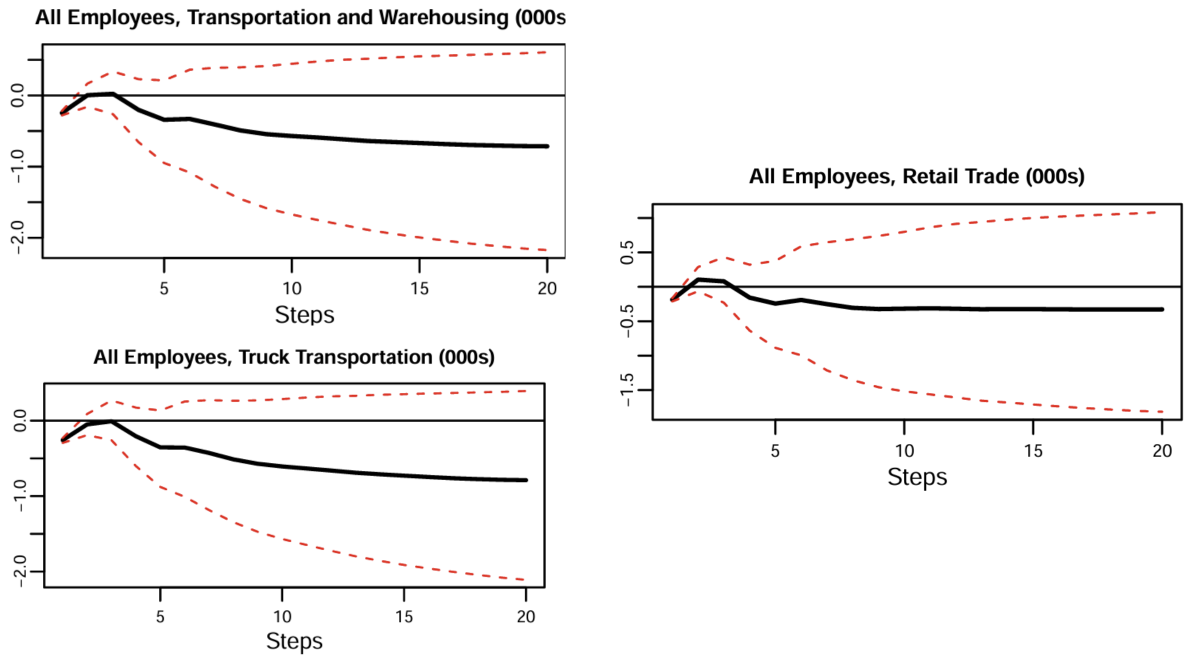


Figure 6: Group (5): Employment and Transportation — IRFs to a negative industrial production shock.

Variables related to employment and transportation such as total employment in transportation and warehousing and vehicle miles traveled tend to decline on average after a negative industrial production shock. The responses imply that weaker production reduces labor demand and freight movement. This pattern highlights how downturns in industrial activity spread into logistics and employment conditions in the real economy.

6 CFAVAR

6.1 Motivation and inspiration from previous litterature

The Conditional Factor-Augmented Vector Autoregression (CFAVAR) comes from the need to combine the structural interpretability of conditional VAR forecasting with the high-dimensional information extraction capabilities of dynamic factor models (DFMs). The central motivation is to allow the researcher to impose specific paths or scenarios on a subset of observable variables such as a preannounced monetary policy rate, a target inflation path—and, or any other plausible future value driven by a few latent common factors. It can also be used - and was developed to this extent - by industries so they can minimize their draw-downs by estimating ”worse case” scenarios on a macro variable of their choice.

The idea of conditioning forecasts within a VAR framework originates from Waggoner and Zha (1998), who developed a Bayesian methodology for producing predictive distributions conditional on specified paths of one or more variables. Their approach introduced a probabilistic treatment of uncertainty and by distinguishing between “hard” and “soft” conditioning. Hard conditions fix future values of selected variables exactly, while soft conditions constrain them within plausible intervals. For now, the CFAVAR model is used uniquely for hard forecast but can be adapted on soft conditioning.

Despite its flexibility, the Bayesian conditional VAR framework faces computational and dimensionality challenges when applied to large systems. The Monte Carlo methods used to enforce conditional paths become computationally expensive. In contrast, earlier approaches such as Clarida and Coyle (1984) relied on state-space representations and Kalman filtering for conditional forecasting in smaller VAR settings. These methods allowed for efficient recursive updating and explicit modeling of measurement uncertainty, but they lacked the ability to integrate information from hundreds of interrelated observables.

The CFAVAR framework bridges these models. It extends the FAVAR model (which already combines a VAR structure with latent factors extracted from large datasets) by embedding it in a fully dynamic, state-space form estimated through the Kalman filter and smoother. Conceptually, CFAVAR represents the synthesis of three established components: the information compression of DFMs, the choice of an observable through the FAVAR framework, and the scenario-based forecasting capability of conditional VARs by Kalman Filtering.

6.2 Framework for the implementation of the models

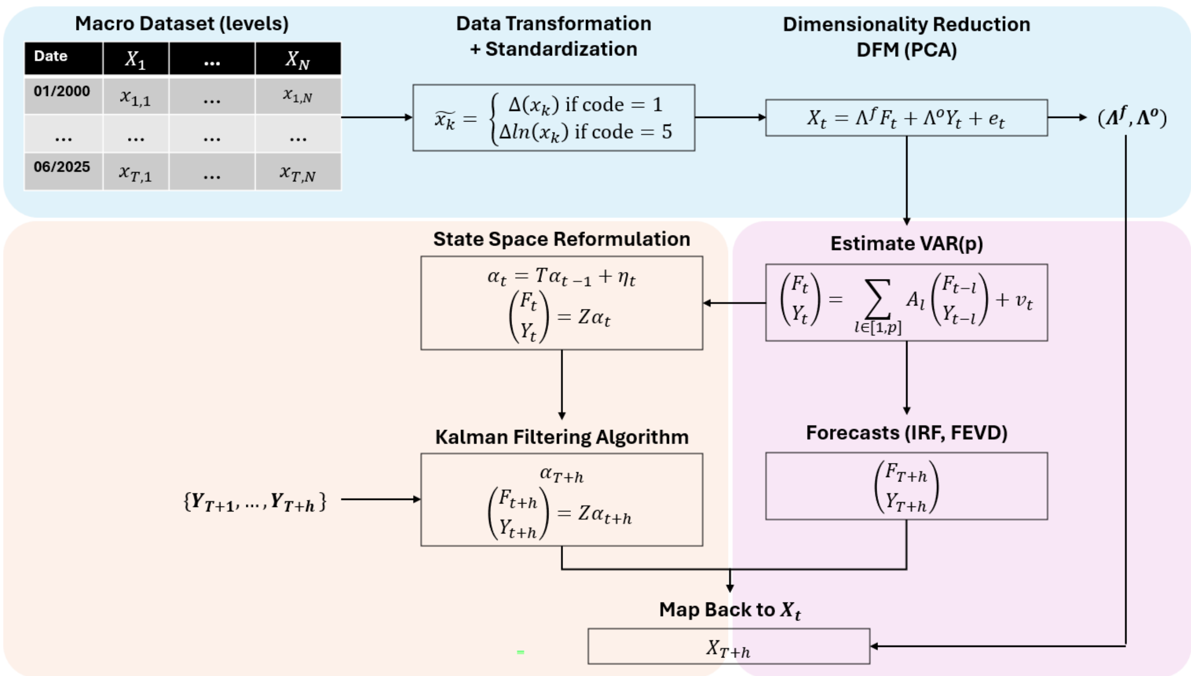


Figure 7: Conceptual Basis

Kalman Filter
Data Preprocessing
FAVAR Model

6.3 Kalman Filtering and Conditional Forecasting for the VAR-in-Companion State Space

We consider a four-variable vector autoregression (VAR(1)) of the form

$$\mathbf{z}_t = \begin{bmatrix} F_{1,t} \\ F_{2,t} \\ F_{3,t} \\ Y_t \end{bmatrix} = \mathbf{c} + A_1 \mathbf{z}_{t-1} + \mathbf{v}_t, \qquad \mathbf{v}_t \sim \mathcal{N}(0, \Sigma_u), \tag{4}$$

where $\mathbf{c}$ is a (4×1) intercept vector, A_1 is a (4×4) autoregressive coefficient matrix, and Σ_u is the (4×4) covariance matrix of reduced-form innovations.

The model is estimated using historical data up to time T_0, after which we impose a future path for one of the variables (here, Y_t) for H periods. Conditional forecasts for $(F_{1,t}, F_{2,t}, F_{3,t})'$ are then generated in a coherent, model-consistent manner using the Kalman filter and RTS smoother. The following equations can be generalized with a VAR(p) model, with p lags, the only difference will be in the expression of the state and observation equations.

6.3.1 State-Space Representation of the VAR(1)

Equation (4) can be recast as a linear Gaussian state-space system. Let the unobserved state vector be defined as

$$\boldsymbol{\alpha}_t = \mathbf{z}_t,$$

so that the model can be written as:

$$\text{(State equation)} \quad \boldsymbol{\alpha}_t = \mathbf{d} + T\boldsymbol{\alpha}_{t-1} + \boldsymbol{\eta}_t, \qquad \boldsymbol{\eta}_t \sim \mathcal{N}(0, Q), \tag{5}$$

$$\text{(Observation equation)} \quad \mathbf{z}_t = Z\boldsymbol{\alpha}_t. \tag{6}$$

The state-space parameters are directly mapped from the VAR(1) coefficients (the simplest case):

$$T = A_1, \qquad Q = \Sigma_u, \qquad Z = I_4, \qquad \mathbf{d} = \mathbf{c}.$$

Hence, each state element $\alpha_{i,t}$ corresponds to an observable variable, but in the forecasting horizon certain components may be treated as missing data ($F_{1,t}, F_{2,t}, F_{3,t}$ when only Y_t is fixed).

6.3.2 Initialization

To start the recursion, the state vector and covariance are initialized as diffuse priors:

$$a_{0|0} = \mathbf{E}[\boldsymbol{\alpha}_0] = \mathbf{0}_4, \qquad P_{0|0} = \mathrm{Var}[\boldsymbol{\alpha}_0] = 10^6 I_4.$$

This ensures non-informative initial conditions, equivalent to assuming maximal prior uncertainty on the initial state.

6.3.3 Kalman Filter with Partial Observations

The Kalman filter provides a recursive method for computing the conditional mean and covariance of the latent state given observations up to time t. Let

$$a_{t|t-1} = \mathbf{E}[\boldsymbol{\alpha}_t | \mathbf{z}_{1:t-1}], \qquad P_{t|t-1} = \mathrm{Var}[\boldsymbol{\alpha}_t | \mathbf{z}_{1:t-1}],$$

denote the predicted mean and covariance. Similarly,

$$a_{t|t} = \mathbf{E}[\boldsymbol{\alpha}_t|\mathbf{z}_{1:t}], \qquad P_{t|t} = \mathrm{Var}[\boldsymbol{\alpha}_t|\mathbf{z}_{1:t}],$$

denote the filtered quantities after incorporating information at time t.

6.3.4 Prediction step. (using the VAR model to predict the unrestricted future values)

The model dynamics imply:

$$a_{t|t-1} = d + T a_{t-1|t-1}, \tag{7}$$

$$P_{t|t-1} = T P_{t-1|t-1} T' + Q. \tag{8}$$

6.3.5 Update step (taking into consideration the future steps for the observable)

Let $\mathcal{O}_t$ denote the set of observed components of $\mathbf{z}_t$, and let Z_t be the corresponding submatrix of Z. For the CFAVAR model, we set that only one path is known: $\mathcal{O}_t = [Y_t]$. In this specific case, we set: $Z_t = [0 \quad 0 \quad 0 \quad 1]$.

The innovation and its covariance are respectively:$v_t = \mathbf{z}_{t,\mathcal{O}} - Z_t a_{t|t-1}$ and $F_t = Z_t P_{t|t-1} Z_t'$. More specifically, in the case of a VAR(1):

$$v_t = Y_t - [0 \quad 0 \quad 0 \quad 1] \cdot \begin{bmatrix} a^{F_1}_{t|t-1} \\ a^{F_2}_{t|t-1} \\ a^{F_3}_{t|t-1} \\ a^{Y}_{t|t-1} \end{bmatrix}, \tag{9}$$

$$v_t = Y_t - a^{Y}_{t|t-1}, \tag{10}$$

$$F_t = [0 \quad 0 \quad 0 \quad 1] P^{(4\times4)}_{t|t-1} \begin{bmatrix} 0 \\ 0 \\ 0 \\ 1 \end{bmatrix} \tag{11}$$

$Y_t - a^{Y}_{t|t-1}$ implements the known information in the system and F_t estimates the updated covariance. In this specific case with a VAR(1) process, v_t is a scalar. The Kalman gain matrix is then

$$K_t = P_{t|t-1} Z_t' F_t^{-1},$$

and the updated moments are:

$$a_{t|t} = a_{t|t-1} + K_t v_t, \tag{12}$$

$$P_{t|t} = P_{t|t-1} - K_t F_t K_t'. \tag{13}$$

When $\mathbf{z}_t$ contains missing entries (such as the future values of $F_{1,t}, F_{2,t}, F_{3,t}$), the corresponding rows are excluded from Z_t, and the update is based solely on the observed components. If no element is observed at time t, the update step is omitted, and $a_{t|t} = a_{t|t-1}$ and $P_{t|t} = P_{t|t-1}$.

The Kalman filter thus propagates the known information iteratively on Y_t forward through the model's transition matrix T and contemporaneous covariances in Q. The forward pass delivers filtered state estimates $\{a_{t|t}, P_{t|t}\}_{t=1}^{T_0+H}$ that reflect both historical data and imposed future paths.

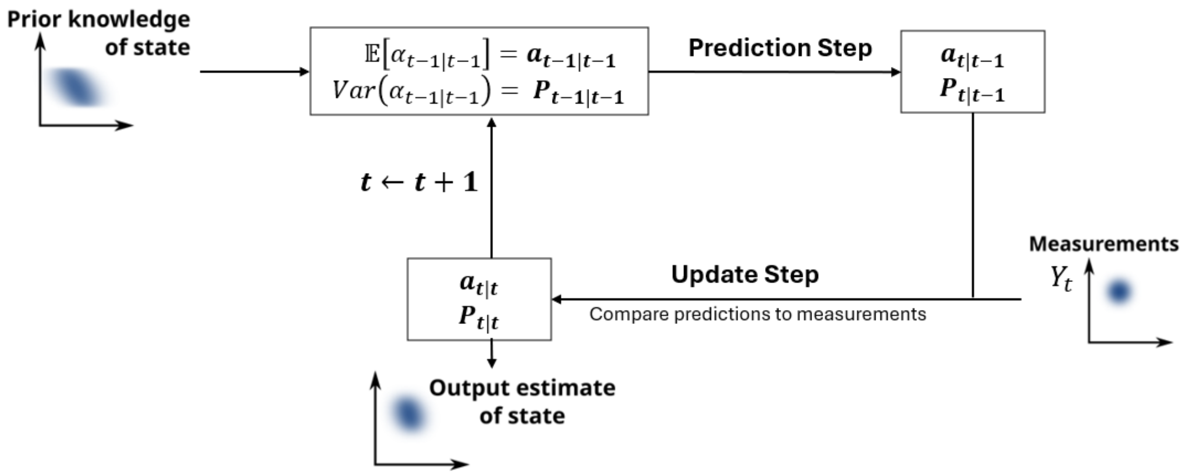


Figure 8: Kalman Filtering

6.4 Rauch–Tung–Striebel Smoother

The Rauch–Tung–Striebel (RTS) smoother refines the filtered estimates by incorporating the entire set of observations $\mathbf{z}_{1:T}$, including future constraints. It proceeds backward from $t = T$ to $t = 1$ using:

$$J_t = P_{t|t}T'(P_{t+1|t})^{-1}, \tag{14}$$

$$a_{t|T} = a_{t|t} + J_t(a_{t+1|T} - a_{t+1|t}), \tag{15}$$

$$P_{t|T} = P_{t|t} + J_t(P_{t+1|T} - P_{t+1|t})J_t'. \tag{16}$$

Here $a_{t|T}$ and $P_{t|T}$ denote the smoothed mean and covariance:

$$a_{t|T} = \mathbf{E}[\boldsymbol{\alpha}_t|\mathbf{z}_{1:T}], \qquad P_{t|T} = \mathrm{Var}[\boldsymbol{\alpha}_t|\mathbf{z}_{1:T}].$$

The matrix J_t (the “smoothing gain”) controls how much the future information from $\boldsymbol{\alpha}_{t+1}$ feeds back into the estimate at t. This backward recursion ensures that information from the future path of Y_t influences not only contemporaneous but also lagged expectations of $(F1_t, F2_t, F3_t)'$, producing a dynamically consistent conditional forecast.

6.5 Extracting Conditional Forecasts

The smoothed states provide the conditional expectations and variances of the observable variables: $\widehat{\mathbf{z}}_t = Za_{t|T}$, and $S_t = ZP_{t|T}Z'$. $\widehat{\mathbf{z}}_t$ is the smoothed conditional mean and S_t is corresponding mean square error matrix (yielded by the observation equation).

6.6 From Conditional States to the Large Panel

After obtaining the compact conditional forecasts, the large panel $\mathbf{X}_t$ is reconstructed using static loadings: $E\left[\mathbf{X}_{T+h}^{(c)}\right] = \widehat{\Lambda} \cdot \widehat{\mathbf{z_{T+h}}}$, with $\widehat{\Lambda} = (\widehat{\Lambda}^f, \widehat{\Lambda}^o)$. Followed by de-standardization and inverse differencing/exponentiation as appropriate to return to levels. Similarly, the forecast covariance matrix is: $\mathrm{Var}(\mathbf{X_{T+h}}) = \widehat{\Lambda} S_{T+h} \widehat{\Lambda}'$.

In this section, the observation equation is set as a hard constraint, the more commonly found expression in literature can be expressed as $z_t = Z\alpha_t + \zeta_t$. With ζ_t following a normal distribution with mean 0 and covariance R. Setting $R = 0$ on constrained entries enforces the path exactly (hard conditioning). Allowing small positive variances in R yields *soft* conditioning that accommodates factor-estimation error or tolerance bands.

6.7 Rolling-Window Backtesting and Forecast Evaluation Framework

To assess the predictive performance of the FAVAR and CFAVAR frameworks against a Random Walk + Drift (RW) benchmark, a recursive rolling-window forecasting design is implemented. This procedure ensures that each forecast uses only information available at the corresponding time, thus avoiding look-ahead bias. This procedure is common in macroeconomic forecasting (see Stock and Watson (2006) - Forecasting With Many Predictors). The outputs and tables follow the procedure implemented by Banbura et al. (2015).

6.7.1 Rolling estimation and forecasting

Let W denote the total number of rolling windows, and t_w the final observation in window w. For each $w = 1, \ldots, W$, the following steps are performed:

1. Estimating the model at each timestep: Using data $\{1, \ldots, t_w\}$, the FAVAR and CFAVAR models are re-estimated. The underlying panel of transformed and standardized variables, $\mathbf{X}_t$, is constructed according to the transformation codes (first differences or log-differences) and then scaled to zero mean and unit variance. Principal components are extracted from the standardized dataset to obtain the estimated factors. A VAR(1) is then estimated on the compact system $\mathbf{z}_t = (F_{1,t}, F_{2,t}, F_{3,t}, Y_t)'$.

2. Generating out of sample forecasts: Out-of-sample forecasts are produced for horizons $h = 1, 2, 4$:
$$\widehat{\mathbf{X}}^{(m)}_{t_w+h|t_w}, \quad m \in \{\text{FAVAR}, \text{CFAVAR}, \text{RW}\}.$$
   - FAVAR forecasts are generated via the estimated VAR(1) in the latent space, de-standardized and inverse transformed to return to levels.
   - CFAVAR forecasts are computed using the CFAVAR framework, with enforcing the realized future path of the conditioning variable $Y_{t+1:t+H}$. It is also, de-standardized and inverse transformed to return to levels.
   - RW + drift forecasts are constructed from the historical mean of first differences for each series:
$$\widehat{X}^{(\text{RW})}_{t+h|t} = X_t + h \cdot \bar{\Delta X}.$$
     With $\bar{\Delta X}$ the historical mean of the first differences.

3. Forecast errors computations: Forecast errors are defined as
$$e^{(m)}_{t_w+h,j} = X_{t_w+h,j} - \widehat{X}^{(m)}_{t_w+h|t_w,j},$$
   for each variable j and model m.

6.7.2 Mean Squared Error and relative performance

For each variable j and forecast horizon h, the Mean Squared Error (MSE) is computed across all rolling windows:

$$\mathrm{MSE}_{j,h}^{(m)} = \frac{1}{W} \sum_{w=1}^{W} \left(e_{t_w+h,j}^{(m)} \right)^2 .$$

Performance ratios are then obtained as

$$\mathrm{Ratio}_{j,h}^{(\mathrm{FAVAR/CFAVAR})} = \frac{\mathrm{MSE}_{j,h}^{(\mathrm{FAVAR})}}{\mathrm{MSE}_{j,h}^{(\mathrm{CFAVAR})}}, \qquad \mathrm{Ratio}_{j,h}^{(\mathrm{CFAVAR/RW})} = \frac{\mathrm{MSE}_{j,h}^{(\mathrm{CFAVAR})}}{\mathrm{MSE}_{j,h}^{(\mathrm{RW})}},$$

and similarly for FAVAR/RW comparisons. Ratios below unity indicate superior predictive accuracy of the denominator model.

6.7.3 Efficiency metrics

For each horizon h, the proportion of series with $\mathrm{Ratio}_{j,h} < 1$ measures the relative efficiency of a given model:

$$\mathrm{Efficiency}_{h}^{(m_1/m_2)} = \frac{1}{N} \sum_{j=1}^{N} \mathbb{I}\Big(\mathrm{Ratio}_{j,h}^{(m_1/m_2)} < 1 \Big) ,$$

where $\mathbb{I}(\cdot)$ denotes the indicator function. For instance, $\mathrm{Efficiency}_{h}^{(\mathrm{CFAVAR/RW})}$ quantifies the fraction of variables for which CFAVAR improves upon a Random Walk with drift.

6.8 Model Robustness

Following the framework form the previous section we get the following results for a VAR(1) model with 3 latent factors and one observable (INDPRO). Although backtesting and the reported MSEs summarize in-sample performance, they are not necessarily indicative of out-of-sample predictive accuracy. They should be viewed instead as a general diagnostic of model fit within the estimation sample. We set $W = 100$ and the horizon h to be $\{1, 2, 4\}$.

6.8.1 FAVAR against Conditional FAVAR

The results for this run are indicated in Table 7 (Appendix). As expected the MSE ratio for INDPRO is $+\infty$, because the CFAVAR model imposes a hard conditioning on the future values. The overall results are summarized in the table below:

Table 2: Relative Performance of CFAVAR Compared to FAVAR Benchmark

Forecast Horizon	**Relative Performance**
$T + 1$	0.56
$T + 2$	0.67
$T + 4$	0.87

The table 2 summarizes the relative performance of the Conditional FAVAR (CFAVAR) model compared to the standard FAVAR benchmark when forecasting the INDPRO (Industrial Production Index) variable. At shorter horizons ($T + 1$), CFAVAR achieves about 55.7% of the benchmark's efficiency. Signifying that there is not a major improvement in the short term of using a FAVAR model against a Conditional Model. As the forecast horizon extends, its performance improves substantially, reaching 66.9% at $T + 2$ and up to 86.8% at $T + 4$. This pattern indicates that the CFAVAR model becomes increasingly advantageous relative to the benchmark when forecasting further into the future, implying that conditional information on INDPRO enhances the model's longer-term predictive accuracy.

6.8.2 Relative Performance of FAVAR Compared to a Random Walk + Drift

The results for this run are indicated in Table 7 (Appendix). In this instance, INDPRO Ratio is not infinity, as we assume no prior knowledge on its future path.

Table 3: Relative Performance of FAVAR Compared to Random Walk with Drift

Forecast Horizon	**Relative Performance**
$T + 1$	0.39
$T + 2$	0.29
$T + 4$	0.14

The table presents the relative efficiency of the FAVAR model when compared to a Random Walk with drift benchmark. Across all horizons, the efficiency values are well below 1, implying that the FAVAR model performs significantly worse than the Random Walk in forecasting the target variable INDPRO.

In the short term ($T + 1$), the FAVAR achieves only about 39% of the Random Walk's forecast accuracy. This efficiency deteriorates further at longer horizons—falling to 29% for two-step forecasts and just 14% for four-step forecasts. This steady decline highlights the Random Walk's robustness as a baseline forecasting model.

A Random Walk with drift assumes that future changes are unpredictable and primarily driven by stochastic shocks rather than systematic patterns. In macroeconomic time series, such as industrial production or inflation, a substantial portion of variation is often persistent and dominated by noise, making complex models prone to overfitting or misidentifying short-term fluctuations as structural information. Over longer horizons, this noise accumulates, and models like FAVAR (while potentially better at capturing contemporaneous relationships) tend to lose predictive power.

As a result, the Random Walk often serves as a strong and difficult-to-beat benchmark in empirical macroeconomic forecasting, especially when the data-generating process exhibits high persistence and limited signal-to-noise ratio. See Kilian (2003), who details the difficulties of models to beat the Random Walk for Exchange Rates, but can be generalized for a larger set of time series.

6.8.3 Relative Performance of CFAVAR Compared to a Random Walk + Drift

The results for this run are indicated in Table 2 (Appendix).

Table 4: Relative Performance of CFAVAR Compared to Random Walk with Drift

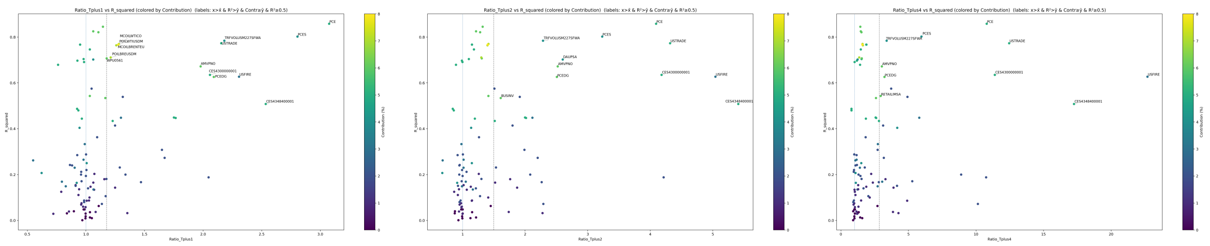
Forecast Horizon	**Relative Performance**
$T+1$	0.56
$T+2$	0.57
$T+4$	0.63

The Conditional Factor-Augmented VAR (CFAVAR) demonstrates superior forecasting performance compared to the Random Walk (RW) benchmark at all horizons.

These results suggest that as the forecast horizon extends, the CFAVAR model maintains and even strengthens its relative predictive advantage over the Random Walk, capturing persistent structural and informational dynamics that the RW model, by design, cannot exploit.

Discussion:
While the CFAVAR exhibits improved efficiency relative to the Random Walk, it is essential to emphasize that the model's purpose is not to serve as a pure forecasting mechanism. Instead, it functions as an analytical tool designed to estimate *conditional* outcomes: how key macroeconomic variables may evolve given specific shocks or policy paths.

6.9 Analytical Results from Forecast Efficiency Ratios (FAVAR, CFAVAR)



T +1 T +2 T +4

Figure 9: Forecast efficiency by horizon (FAVAR vs cFAVAR).

Across all horizons (T+1, T+2, and T+4), the mean squared error (MSE) ratios show that the cFAVAR model performs better than the FAVAR for most high-R^2 variables, confirming that conditioning on industrial production improves forecast accuracy. This result is intuitive because the conditioning variable, industrial production, acts as a key driver of real economic activity, allowing the model to capture structural linkages across consumption, trade, and employment. Since CFAVAR explains a larger portion of the variation in these variables, its conditional structure enhances predictability over time.

The variables that consistently appear across all three horizons with ratios above the average include PCE (Personal Consumption Expenditures, representing household spending), USTRADE (total U.S. trade activity, capturing import and export flows), USFIRE (employment in financial activities, reflecting credit and investment-related labor demand), CES4300000001 (All Employees: Retail Trade), and CES4348400001 (All Employees: Truck Transportation). Among them, the largest performance gains occur in USFIRE, CES4348400001, and CES4300000001, which show the strongest rightward shifts in the ratio as the forecast horizon extends. This indicates that industrial production information significantly improves forecast accuracy for employment in both financial and goods-related sectors. USTRADE and PCE also show persistent improvement, suggesting that conditioning on production enhances the model's ability to track aggregate demand and trade activity. Overall, these results demonstrate that CFAVAR's advantage comes from its ability to integrate production-driven information, leading to more accurate forecasts across sectors directly or indirectly linked to real economic activity.

7 Case Study: Conditional Forecasting of Ford Sales Under Industrial Production Shocks

7.1 Objective and Methodology

The purpose of this case study is to assess the sensitivity of monthly Ford vehicle sales in the United States to a hypothetical decline in industrial production (INDPRO). Such a decline could arise under several plausible macroeconomic or industry-specific scenarios such as recessions, major supply chain disruptions, energy price shocks or structural transitions.

In this analysis, we simulate a hypothetical six-month conditional decline in industrial production under these potential circumstances and study the corresponding effects on Ford's sales forecast and inventories using the CFAVAR framework. The conditional path of the Industrial Production Index (INDPRO) is specified as: $INDPRO_{T+h} = [100, 97, 95, 93, 90, 89]$, representing a sustained decline in industrial activity over the next six months.

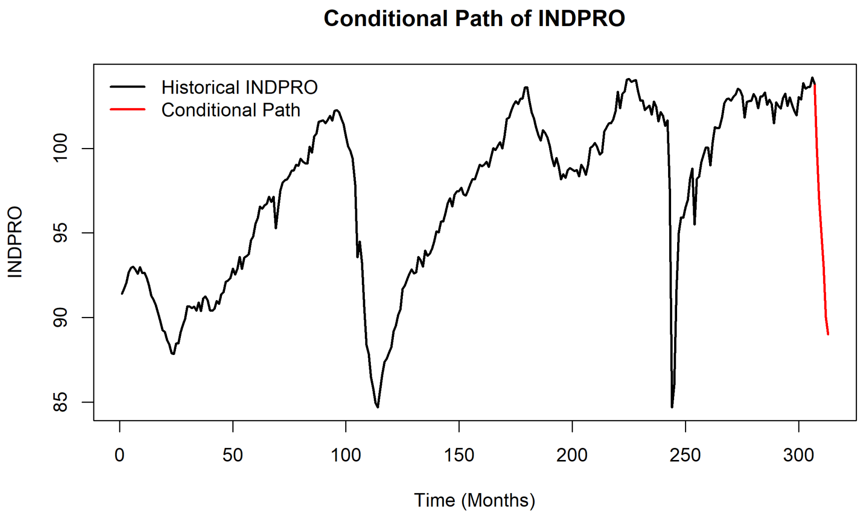


Figure 10: INDPRO and Conditional Forecast

7.2 Comparison of Ford Forecast Methods

In the first part, two alternative approaches are considered for estimating Ford sales conditional on the decline in industrial production.

1. Scaled TOTALSA. The total U.S. vehicle sales (TOTALSA) series is scaled to match the most recent level of Ford sales. This assumes Ford sales evolve proportionally to aggregate vehicle sales under macroeconomic shocks (which is a naive approach).

2. CFAVAR Direct Forecast. Ford's own sales (FORD) forecast is derived directly from the CFAVAR system reflecting both its historical correlation structure and the imposed INDPRO path.

Figure 11 shows the baseline equal-comparison scenario.

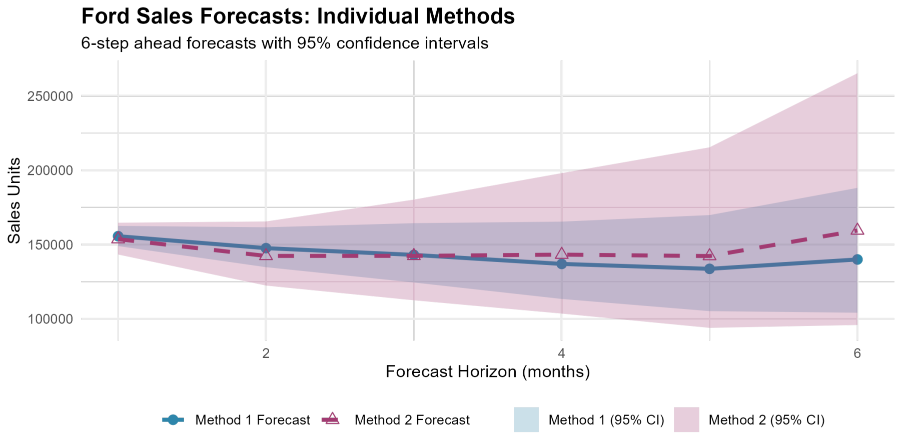


Figure 11: Forecast Comparison - Scaled TOTALSA vs FORDSA

Method 1 (Scaled TOTALSA) appears to deliver superior forecasting performance. However, this result requires careful interpretation in light of the underlying model dynamics and backtesting evidence.

The out-of-sample backtests for the CFAVAR model reveal that aggregate vehicle sales (TOTALSA) exhibit substantially higher predictive accuracy than Ford sales directly, with MSE Ratios against RW of $[0.88, 0.74, 0.58]$ (up to horizon of 4) compared to their direct FORD equivalents (closer to 1). This differential performance arises because Ford sales are influenced by factors beyond macroeconomic conditions captured by the CFAVAR system. Specifically, company-specific decisions (production directives, inventory management policies, marketing campaigns, and strategic business initiatives) exert a direct influence on Ford's sales dynamics that are not readily interpretable through macroeconomic variables alone.

In contrast, aggregate vehicle sales (TOTALSA) function as a smoothed, economy-wide measure that is more closely aligned with macroeconomic drivers. By scaling TOTALSA to Ford's baseline level, Method 1 effectively leverages the stronger relationship between industrial production and aggregate market dynamics. While this approach may appear less direct than applying the full CFAVAR system to Ford sales, it proves more robust empirically because it avoids attempting to capture idiosyncratic firm-level factors through macroeconomic variables.

This finding underscores an important principle in conditional forecasting: a simpler method that exploits the strongest available macroeconomic relationship may outperform a more complex system that attempts to model variables containing substantial non-macroeconomic noise. The scaled TOTALSA approach thus represents a middle ground between naive forecasting and potentially overspecified structural modeling.

While sales metrics provide insights into consumer demand, inventory levels offer a complementary perspective on the transmission of shocks through production and supply-chain constraints. Figure 12 presents six-month ahead forecasts of Ford inventory under the specified decline in industrial production.

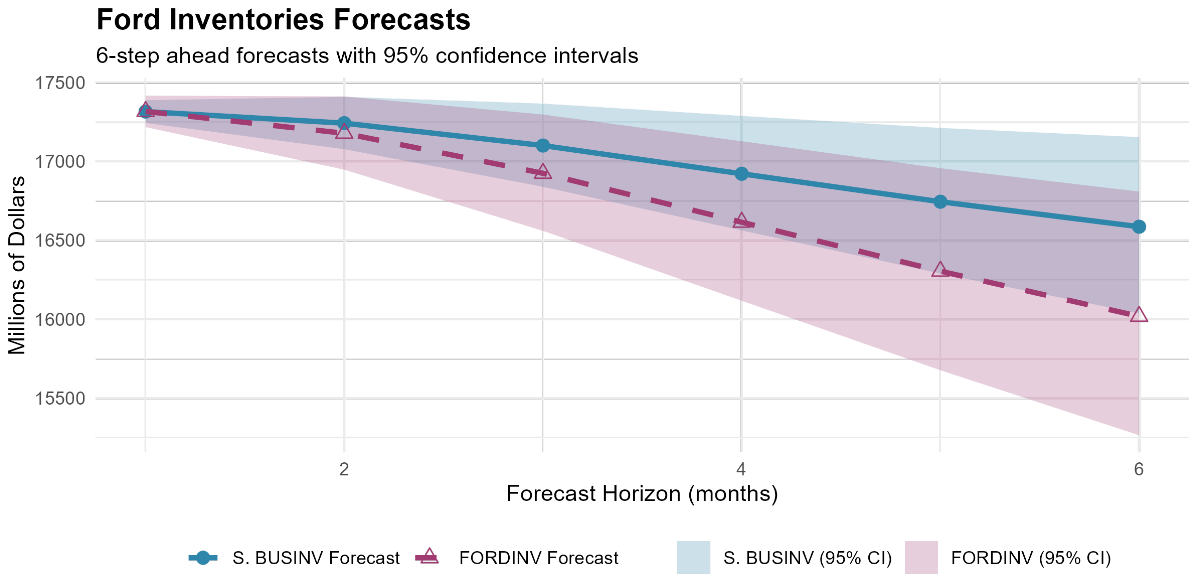


Figure 12: Ford Inventories - Scaled BUSINV vs FORDINV

The inventory forecasts reveal a different pattern compared to Ford sales. While sales remain relatively resilient over the forecast horizon (reflecting persistent consumer demand for automobiles in the U.S. market) both measures of Ford inventory experience a substantial and persistent decline. Specifically, both the scaled total business inventories (S. BUSINV) and Ford's direct inventory holdings (FORDINV) exhibit downward trajectories, with cumulative declines of approximately 750 to 1,250 million dollars across the six-month forecast period.

This divergence between sales and inventory behavior carries important implications. In a demand-driven recession, both sales and inventories would fall together as producers cut back on production in response to weakening customer demand. However, the observed pattern—where inventories contract sharply while sales remain stable—reflects a supply-side shock transmitted through industrial production. When industrial production declines, manufacturers face constraints in sourcing inputs and materials needed for vehicle production. Ford responds by drawing down existing inventory stocks to fulfill customer orders, even as demand remains relatively stable.

7.3 Forecasts Under Multiple Conditions

In this section, we will expand on the initial assumption that $\mathbf{Y_t}$ is dimension 1×1 by adding another observable: Real Gross Domestic Product (GDPM, S&P's converted monthly Real GDP in Billion Dollars).
For this scenario, we examine Ford sales and inventory forecasts under a joint conditional shock where both Gross Domestic Product (GDPM) and Industrial Production (INDPRO) experience coordinated declines. The conditional paths are specified as:

$$\text{GDPM}_{T+h} = [23730, 23580, 23450, 23330, 23250, 23200] \text{ (in Billion Dollars)} \tag{17}$$
$$\text{INDPRO}_{T+h} = [100, 97, 95, 93, 90, 89] \text{ (index)} \tag{18}$$

This joint scenario represents a demand-driven macroeconomic contraction wherein both aggregate economic activity (GDP) and productive capacity (industrial production) decline in tandem, mimicking a classical recession dynamic.

Assuming (for the Cholesky decomposition) that Gross Domestic Product can impact INDPRO index(but not reciprocally): $\mathbf{Y_t} = (\text{GDPM}_t, \text{INDPRO}_t)'$. The framework for the CFAVAR is the same independently of the number of observables. Both forecasts are generated using the two methods detailed in the beginning of this section (Figures 13 and 14).

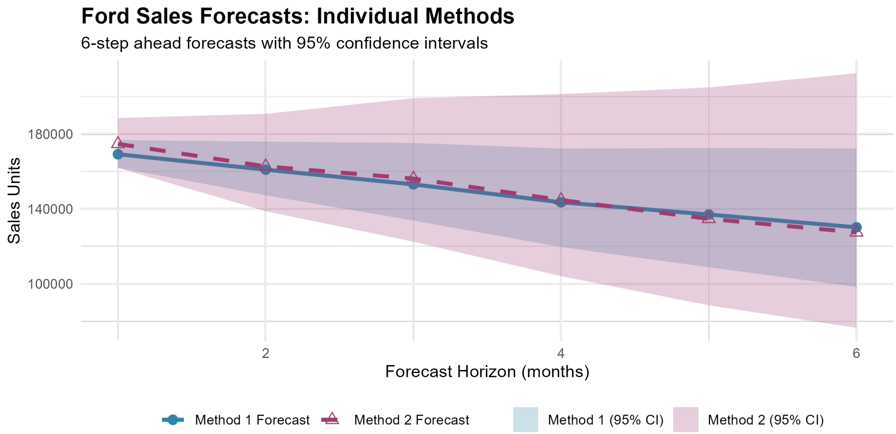


Figure 13: Ford Sales, Scaled TOTALSA vs FORDSA

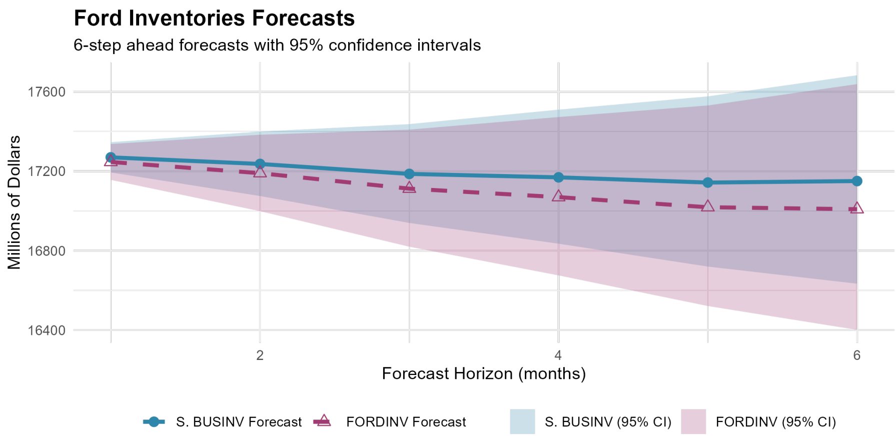


Figure 14: Ford Inventory, Scaled BUSINV vs FORDINV

Ford sales forecasts under the joint GDP-INDPRO decline exhibit a substantial and sustained contraction over the six-month horizon. Both the scaled TOTALSA and direct CFAVAR-based FORD forecasts display significant downward trajectories, reflecting reduced consumer purchasing power and weakened aggregate demand as real economic output contracts.

In sharp contrast to the inventory behavior observed under the isolated INDPRO decline, inventory levels remain relatively stable throughout the forecast period under the joint scenario. Both scaled business inventories (S. BUSINV) and Ford's direct inventory holdings (FORDINV) exhibit minimal cumulative change.

This divergent pattern between the two scenarios illuminates a fundamental distinction in how supply-side and demand-side macroeconomic shocks propagate through the automotive industry:

- When industrial production declines in isolation (input constraints, major supply chain disruptions, or production capacity constraints) downstream manufacturers like Ford face material sourcing difficulties. If aggregate demand remains stable (as proxied by stable GDP), consumer demand for vehicles persists. Ford must therefore draw down existing inventory reserves to fulfill orders while production capabilities are constrained. This generates the observed inventory decline coupled with relatively stable sales. The firm depletes its buffer stocks to maintain sales in the face of production frictions.

- When both GDP and industrial production decline together (signaling a coordinated macroeconomic contraction where purchasing power erodes in parallel with productive capacity) consumers reduce vehicle purchases. Faced with declining demand, Ford has no incentive to draw down inventory significantly. Instead, the firm naturally maintains inventory levels more stable as sales volume contracts and industrial production slows down. The inventory cushion becomes less relevant because the binding constraint is no longer production capacity but rather customer willingness to purchase.

This example shows the value of conditional forecasting frameworks that can decompose complex macroeconomic scenarios into their constituent components and trace their differential impacts on firm-level outcomes.

7.4 Market Share Scaling Approach

To improve realism, the second part introduces a market-share-based scaling. TOTALSA is rescaled by a random uniform market share between 11% and 13%, representing Ford's typical U.S. market share. $\text{FORD}_{T+h} = \text{TOTALSA}_{T+h} \times s, \text{with} s \sim \mathcal{U}(0.11, 0.13)$

1. TOTALSA scaled by uniform share $\in$ [11%, 13%].
2. CFAVAR Ford-specific forecast sales, same as before.

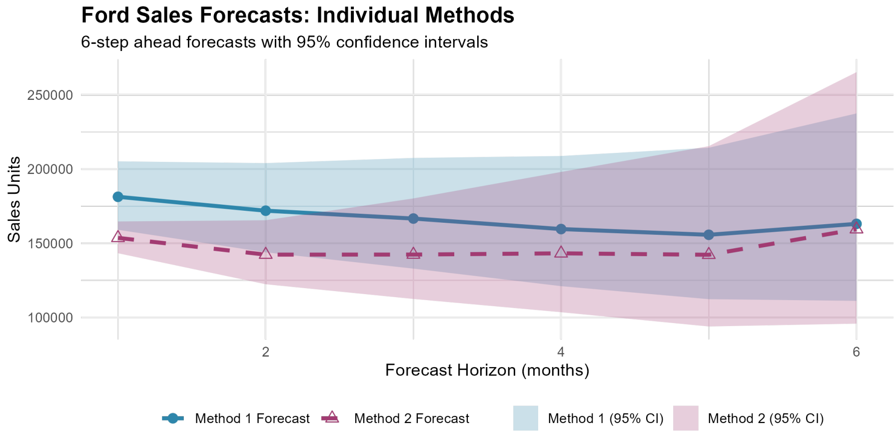


Figure 15: Model Comparison – Ford Case Study 1

The introduction of stochastic market share captures an important source of forecast uncertainty that deterministic scaling neglects. By parameterizing market share as a uniform random variable rather than a fixed coefficient, the methodology acknowledges that Ford's ability to capture aggregate vehicle demand depends on factors beyond macroeconomic conditions. These include competitive dynamics, product-specific demand shifts, promotional intensity, supply allocation decisions, and other strategic firm-level actions that influence Ford's market position.

The direct consequence of this approach is a substantial widening of the confidence intervals around the scaled TOTALSA forecasts (Method 1) relative to the deterministic scaling scenario. This expanded uncertainty band reflects the genuine unpredictability inherent in how firm-specific decisions translate aggregate market conditions into individual firm outcomes. The uniform distribution choice preserves the empirical range of Ford's historical market share.

The widened confidence intervals under market-share scaling provide a more candid representation of true forecast uncertainty when translating macroeconomic scenarios to firm-level outcomes, making this approach particularly valuable for risk assessment and scenario analysis applications.

8 Conclusion

This study demonstrates the value of factor-augmented approaches for understanding and forecasting macro-financial dynamics in complex systems. Empirical results confirm that common latent factors extracted from a large macroeconomic panel explain a substantial share of the observed variation across variables, validating the suitability of this framework for policy and business applications.

The conditional forecasting experiments highlight the practical relevance of the CFAVAR methodology under simulated industrial production shocks and specific paths. This approach captures the dominant macroeconomic transmission channels while maintaining empirical robustness. The introduction of stochastic market-share scaling further enhances realism by reflecting the uncertainty inherent in competitive and strategic firm behavior.

Overall, the results illustrate that macro-driven conditional forecasting, when combined with aggregation and appropriate stochastic modeling, can yield valuable insights for both policy evaluation and corporate risk assessment. The CFAVAR framework provides a versatile foundation for future extensions in forecasting, scenario analysis, and strategic planning.

A Appendix:

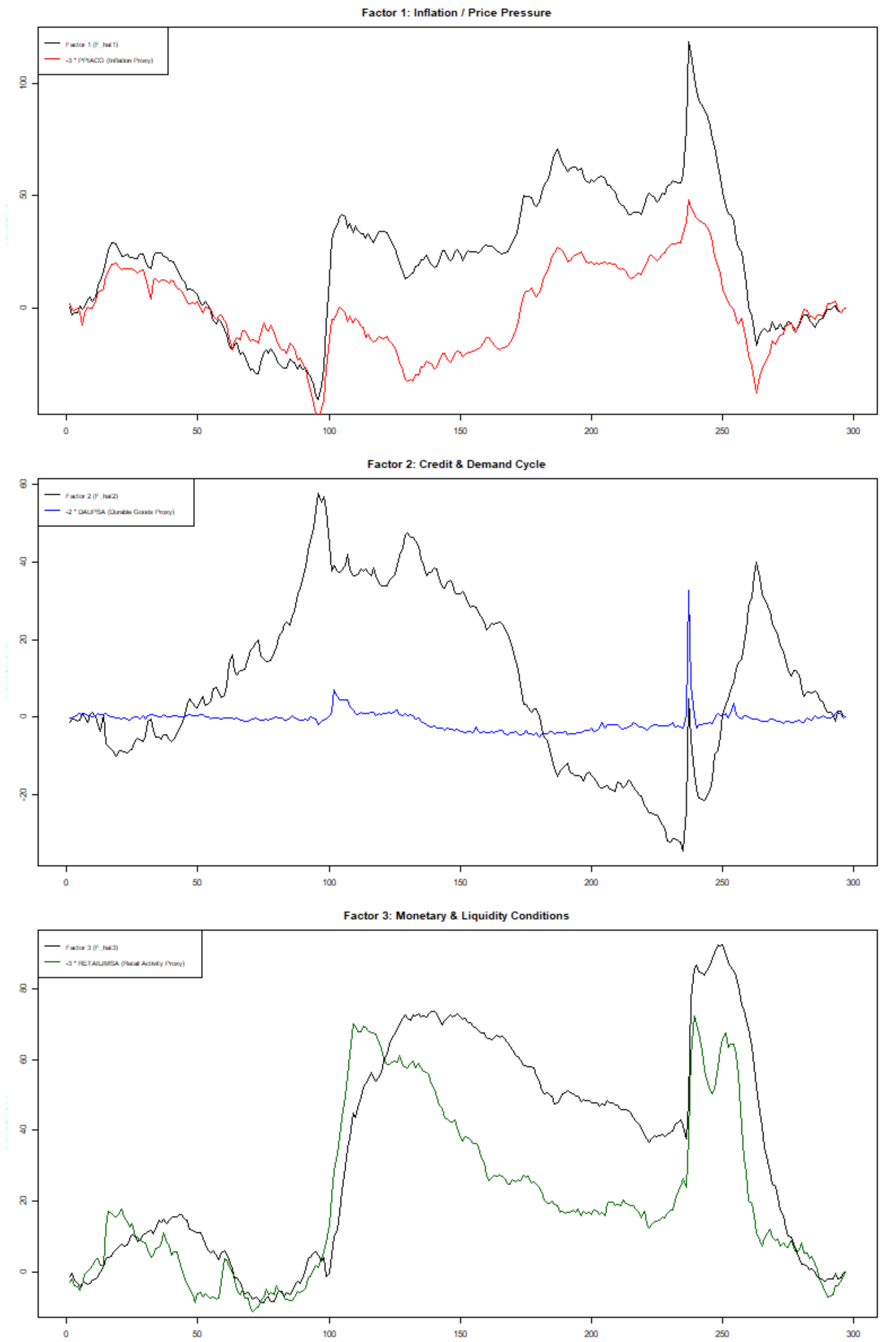


Figure 16: Cumulative plots of the three latent factors $\hat{F}_1$, $\hat{F}_2$, and $\hat{F}_3$, each compared with representative macroeconomic reference variables (PPIACO, DAUPSA, and RETAILIMSA, respectively).

Table 5: Correlation of Variables with Factors

Factor	Variable	Correlation (abs value)
F1	PPIACO	0.815
	PPIIDC	0.808
	PCUOMFGOMFG	0.808
	WPU0561	0.801
	MCOILBRENTEU	0.797
	MCOILWTICO	0.797
	POILWTIUSDM	0.796
	CPIAUCSL	0.780
	CPALTT01USM661S	0.778
	PCEPI	0.775
F2	GASDESM	0.571
	TRFVOLUSM227SFWA	0.553
	PPIACO	0.539
	PCUOMFGOMFG	0.535
	CUUR0000SA0R	0.534
	PPIIDC	0.530
	DAUPSA	0.517
	CPIAUCSL	0.508
	CPALTT01USM661S	0.508
	CPIENGSL	0.490
F3	M1SL	0.673
	M1REAL	0.672
	RETAILIMSA	0.657
	PCEDG	0.532
	BUSINV	0.472
	M2SL	0.462
	REVOLSL	0.457
	SAHMREALTIME	0.457
	CUSR0000SEHA	0.447
	MCOILWTICO	0.428

A.1 IRF Plots

Table 6: Variable Contributions and R^2

Variables	Contribution	R^2
Industrial Production: Total Index	21%	1
Global Price of WTI Crude ($/barrel)	8%	0.767
Crude Oil Prices (WTI) ($/gal)	7%	0.770
Crude Oil Prices: Brent - Europe ($/bar)	7%	0.764
Global price of Brent Crude ($/Barrel)	7%	0.711
PPI : Crude Petroleum (Domestic Production)	6%	0.707
PPI: All Commodities	6%	0.845
PPI : Industrial Commodities	6%	0.821
PPI Total Manufacturing industries	6%	0.825
Retailers Inventories (B$)	6%	0.543
New Orders: Motor Vehicles and Parts (M$)	6%	0.672
Total Business Inventories (M$)	6%	0.534
PCE: Durable Goods (B$)	6%	0.626
CPI for All Urban Consumers	5%	0.767

Table 6: Variable Contributions and R^2 (continued)

Variables	**Contribution**	R^2
Consumer Price Index: Total for United States	5%	0.767
Personal Consumption Expenditures: Chain-type Price Index	5%	0.746
Personal Consumption Expenditures (B$)	5%	0.858
US Diesel Sales Price ($/gal)	5%	0.691
M1 Money Stock (B$)	5%	0.480
CPI : Energy in the US	5%	0.704
Light Weight Vehicle Sales (MU)	5%	0.449
Real M1 Money Stock (B$)	5%	0.487
Total Vehicle Sales (M units)	5%	0.447
US Regular Gas Price ($/gal)	5%	0.697
All Employees, Transportation and Warehousing (000s)	5%	0.635
All Employees, Retail Trade (000s)	5%	0.773
CPI : Purchasing Power of Consumer $ in U.S. City Av.	5%	0.679
PPI : Chemical Manufacturing	5%	0.444
All Employees, Truck Transportation (000s)	5%	0.508
Total Assets, All Commercial Banks (B$)	5%	0.434
Vehicle Miles Traveled (MMiles)	4%	0.784
Personal Consumption Expenditures: Services (B$)	4%	0.802
Domestic Auto Production (000s)	4%	0.702
Bank Credit, All Banks (B$)	4%	0.207
Real-time Sahm Rule Recession Indicator (%)	4%	0.404
PPI: Plastics Material and Resin Manufacturing	4%	0.250
Consumer Sentiment (index)	4%	0.164
Moody's Seasoned Baa Corporate Bond Yield (%)	3%	0.149
Global price of Copper ($/T)	3%	0.333
All Employees, Government (000s)	3%	0.448
PPI : Line Haul Railroads	3%	0.230
All Employees, Financial Activities (000s)	3%	0.627
Loans and Leases in Bank Credit, All Banks (B$)	3%	0.262
10-Year High Quality Market (HQM) Corporate Bond Yield (%)	3%	0.169
PPI : Construction Materials	3%	0.265
Domestic Auto Inventories (000s)	3%	0.135
Global Price of Aluminum ($/T)	2%	0.288
Federal Funds Effective Rates (%)	2%	0.308
Global price of Agr. Raw Material Index	2%	0.285
PPI Metals and Metal Products	2%	0.087
Global price of Natural gas, EU ($/MTEU)	2%	0.080
Global Price for Nickel ($/T)	2%	0.171
Global price of Barley ($/T)	2%	0.194
Global price of Cotton ($c/lbs)	2%	0.200
Global Supply Chain Pressure Index	2%	0.106
M2 Money Stock (B$)	2%	0.575
CPI for All Urban Consumers: All Items Less Food and Energy	2%	0.363
Market Yield on U.S. Treasury Securities (1-Y Constant Maturity)	2%	0.231
Median CPI	2%	0.240
PPI : Food Manufacturing	2%	0.212
Personal Income (B$)	2%	0.072
Revolving Consumer Credit Owned and Securitized (M$)	2%	0.414
Global price of Coal, Australia ($/T)	2%	0.220
New Privately-Owned Housing Units Started: Total Units (000s)	2%	0.167
CPI : Rent of Primary Residence in U.S. City Average	2%	0.242
Long-Term Government Bond Yields: 10-Year US (%)	2%	0.181
S&P 20-City Composite Home Price Index	2%	0.140
Market Value of Marketable Treasury Debt (B$)	2%	0.200
Deposits, All Commercial Banks (B$)	2%	0.539
Bank Prime Loan Rate (%)	2%	0.273
Truck Tonnage Index	2%	0.188
Global price of Palm Oil ($/T)	2%	0.151
S&P CoreLogic Case-Shiller U.S. National Home Price Index	1%	0.154

Table 6: Variable Contributions and R^2 (continued)

Variables	**Contribution**	R^2
PPI: Pulp, Paper, and Allied Products	1%	0.075
Retail Money Market Funds ($B)	1%	0.125
New Privately-Owned Housing Units Under Construction (000s)	1%	0.165
Global price of Corn ($/T)	1%	0.136
Currency in Circulation (B$)	1%	0.203
Total Construction Spending in the United States (M$)	1%	0.180
Used Cars and Trucks in U.S. City Average (index)	1%	0.058
PPI : Farm Products: Grains	1%	0.111
PPI : Deep Sea Freight Transportation	1%	0.087
Total Consumer Credit Owned and Securitized (M$)	1%	0.143
Economic Policy Uncertainty U.S.	1%	0.029
CPI : Food At Home U.S. City Average	1%	0.147
Consumer Loans: All Commercial Banks (B$)	1%	0.037
Population (000s)	1%	0.069
Heavy Weight Trucks (000s)	1%	0.100
1Y Real Interest Rate (%)	1%	0.060
Global price of Wheat ($/T)	1%	0.086
CPI : New Vehicles in U.S. City Average	0%	0.048
CPI : Total for China	0%	0.040
Chinese Yuan Renminbi to U.S. Dollar Spot Exchange Rate	0%	0.048
Electricity per Kilowatt-Hour in U.S. City Average ($)	0%	0.031
10-Y Real Interest Rates (%)	0%	0.036
Price of Olive Oil ($/T)	0%	0.018
Net Auto Sales Ford Motors	0%	0.010
Log Imports From China	0%	0.063
CPI : Medical Care Services in the U.S. Average	0%	0.030
Median Sales Price for New Houses Sold in the U.S. ($)	0%	0.013
UStarCH	0%	0.002
Effective Tariffs	0%	0.009
PPI : Pharmaceutical Preparation Manufacturing	0%	0.001

Table 7: Variable FAVAR MSE / CFAVAR MSE Over Time

Variable	$T+1$	$T+2$	$T+4$
INDPRO	**inf**	**inf**	**inf**
GEPUCURRENT	0.85	0.94	**1.15**
M1SL	0.93	0.86	0.78
M2SL	**1.05**	**1.51**	**3.72**
M1REAL	0.92	0.84	0.78
FEDFUNDS	**1.65**	**1.99**	**2.72**
USTRADE	**2.15**	**4.32**	**12.46**
CPIAUCSL	0.95	**1.15**	**1.89**
CPILFESL	**1.10**	**1.26**	**1.83**
CSUSHPINSA	0.91	**1.02**	**1.28**
PCE	**3.08**	**4.09**	**10.79**
BAA	0.83	0.99	**2.72**
CPALTT01USM661S	0.95	**1.15**	**1.87**
GS1	**1.29**	**1.53**	**1.77**
REAINTRATREARAT10Y	**1.03**	**1.15**	**1.32**
SAHMREALTIME	0.95	**1.14**	**4.17**
CUSR0000SETA02	**1.00**	0.98	**1.04**
CCLACBM027SBOG	**1.35**	**2.28**	**4.26**
UMCSENT	0.92	0.91	**1.10**
PCEPI	**1.03**	**1.18**	**1.47**
HOUST	**1.47**	**2.26**	**2.81**
DPSACBM027SBOG	**1.31**	**1.91**	**4.93**
MCOILWTICO	**1.28**	**1.41**	**1.60**

Variable	$T+1$	$T+2$	$T+4$
TOTALSA	**1.77**	**2.01**	**2.61**
MSACSR	**1.07**	**1.07**	**1.01**
CUSR0000SEHA	0.86	0.95	**1.19**
CUUR0000SETA01	0.99	**1.00**	**1.04**
CUUR0000SA0R	0.76	0.89	**1.42**
CUSR0000SAF11	**1.04**	**1.13**	**1.88**
CPIENGSL	0.98	**1.10**	**1.53**
CUSR0000SAM2	**1.00**	**1.00**	**1.03**
CHNCPIALLMINMEI	0.90	0.88	0.91
PPIACO	**1.14**	**1.32**	**1.44**
WPU0911	0.96	0.98	0.99
PCU325211325211	**1.01**	**1.15**	**1.51**
WPU101707	0.98	0.97	0.96
PCUOMFGOMFG	**1.06**	**1.22**	**1.47**
PCU325325	0.96	**1.20**	**1.85**
WPUSI012011	0.98	**1.02**	**1.16**
PCU311311	0.96	**1.06**	0.95
PCU325412325412	0.97	0.93	0.90
PCU483111483111	**1.03**	**1.15**	**1.50**
PPIIDC	**1.11**	**1.28**	**1.52**
WPU012	0.94	0.92	**1.08**
PCU482111482111	0.90	**1.02**	**1.40**
WPU0561	**1.18**	**1.31**	**1.55**
MPRIME	**1.67**	**2.20**	**3.18**
CURRCIR	**1.07**	**1.26**	**2.24**
EXCHUS	0.98	0.98	0.99
MEDCPIM094SFRBCLE	0.88	0.95	**1.08**
LOANINV	0.62	0.68	**1.08**
LOANS	0.55	0.68	**1.07**
MCOILBRENTEU	**1.26**	**1.40**	**1.63**
GASREGM	0.93	0.99	**1.18**
POPTHM	0.96	0.95	0.94
IRLTLT01USM156N	**1.17**	**1.30**	**1.53**
SPCS20RSA	**1.02**	**1.21**	**1.67**
RMFSL	0.79	0.87	**1.03**
MSPNHSUS	**1.03**	**1.22**	**1.43**
APU000072610	0.84	0.87	**1.23**
TTLCONS	**1.16**	**1.76**	**3.30**
PCOPPUSDM	0.99	0.98	**2.74**
PI	**1.14**	**2.29**	**10.14**
ALTSALES	**1.75**	**2.00**	**2.57**
REAINTRATREARAT1YE	0.98	0.99	**1.30**
POLVOILUSDM	**1.00**	0.99	0.99
HTRUCKSSA	**1.03**	**1.41**	**2.13**
USGOVT	**1.30**	**2.12**	**5.80**
AUINSA	**1.06**	**1.16**	**1.22**
PWHEAMTUSDM	**1.01**	**1.15**	**4.91**
CES4348400001	**2.53**	**5.41**	**17.26**
TLAACBM027SBOG	**1.23**	**1.51**	**2.82**
PCEDG	**2.09**	**2.51**	**3.22**
UNDCONTSA	**1.06**	**1.52**	**2.36**
PNGASEUUSDM	0.98	0.95	0.91
TOTALSL	**1.25**	**1.87**	**3.90**
PALUMUSDM	**1.00**	**1.01**	0.99
POILBREUSDM	**1.21**	**1.30**	**1.36**
PNICKUSDM	0.96	0.99	**5.28**
USEPUINDXM	0.72	**1.00**	**1.20**
TRFVOLUSM227SFWA	**2.18**	**2.29**	**3.39**
PCES	**2.81**	**3.23**	**5.96**
CONSUMER	**1.08**	**1.74**	**3.85**
REVOLSL	**1.25**	**1.80**	**3.13**
DAUPSA	**1.06**	**2.60**	**1.23**

Variable	$T+1$	$T+2$	$T+4$
AMVPNO	**1.98**	**2.52**	**3.03**
BUSINV	**1.17**	**1.61**	**2.60**
CES4300000001	**2.06**	**4.18**	**11.39**
USFIRE	**2.31**	**5.04**	**22.69**
TRUCKD11	**2.05**	**4.21**	**10.75**
PCOALAUUSDM	**1.00**	0.99	0.97
PRAWMINDEXM	0.93	0.92	**1.16**
GASDESM	0.98	**1.00**	**1.02**
PBARLUSDM	**1.00**	**1.00**	**1.45**
PMAIZMTUSDM	0.94	0.94	**1.28**
PPOILUSDM	0.91	0.93	**4.15**
PCOTTINDUSDM	0.96	0.95	**1.30**
POILWTIUSDM	**1.28**	**1.40**	**1.59**
HQMCB10YRP	0.79	**1.05**	**3.06**
RETAILIMSA	**1.03**	**1.41**	**2.94**
MVMTD027MNFRBDAL	**1.34**	**2.08**	**8.90**
FORD	**1.05**	**1.13**	**1.58**
eff_tariff	**1.00**	**1.00**	**1.01**
GSPCI	**1.17**	**1.28**	**2.03**
IMPCH	**1.11**	**1.45**	**2.71**

Table 8: FAVAR vs. RW Relative Ratios Over Time

Variable	$T+1$	$T+2$	$T+4$
GEPUCURRENT	1.01	**0.99**	1.11
M1SL	1.30	1.04	**0.96**
M2SL	**0.85**	1.42	3.43
M1REAL	1.23	**0.98**	**0.92**
FEDFUNDS	1.29	1.59	2.16
USTRADE	1.98	3.77	7.95
CPIAUCSL	**0.68**	**0.88**	1.03
CPILFESL	**0.73**	**0.85**	1.22
CSUSHPINSA	**0.88**	**0.99**	1.27
PCE	1.93	2.77	4.46
BAA	1.06	1.22	2.81
CPALTT01USM661S	**0.68**	**0.88**	1.03
GS1	1.06	1.19	1.34
REAINTRATREARAT10Y	1.03	1.10	1.16
SAHMREALTIME	**0.70**	**0.90**	3.08
CUSR0000SETA02	**0.98**	**0.98**	**0.99**
CCLACBM027SBOG	1.97	3.26	4.70
UMCSENT	1.09	1.26	1.27
PCEPI	**0.75**	**0.87**	**0.91**
INDPRO	1.63	2.87	5.62
HOUST	1.06	1.32	1.67
DPSACBM027SBOG	1.03	1.66	4.29
MCOILWTICO	1.15	1.25	1.16
TOTALSA	1.56	1.49	1.50
MSACSR	**0.98**	**0.97**	**0.88**
CUSR0000SEHA	**0.53**	**0.57**	**0.69**
CUUR0000SETA01	**0.92**	**0.94**	**0.97**
CUUR0000SA0R	**0.82**	1.06	1.31
CUSR0000SAF11	1.02	1.10	1.73
CPIENGSL	**0.95**	1.22	1.35
CUSR0000SAM2	1.05	1.08	1.13
CHNCPIALLMINMEI	**0.98**	1.07	1.18
PPIACO	**0.85**	1.00	1.02
WPU0911	**0.98**	**0.96**	**0.96**

Variable	$T+1$	$T+2$	$T+4$
PCU325211325211	**0.90**	1.09	1.44
WPU101707	1.03	1.00	1.03
PCUOMFGOMFG	**0.89**	1.04	1.10
PCU325325	**0.72**	**0.93**	1.40
WPUSI012011	**0.92**	**0.95**	1.08
PCU311311	1.16	1.17	**0.98**
PCU325412325412	1.11	1.29	1.71
PCU483111483111	1.04	1.13	1.28
PPIIDC	**0.81**	**0.97**	1.05
WPU012	**0.98**	**0.99**	1.11
PCU482111482111	**0.92**	**0.97**	1.44
WPU0561	1.01	1.20	1.15
MPRIME	1.34	1.69	2.46
CURRCIR	1.07	1.44	2.39
EXCHUS	**0.99**	**0.99**	**0.99**
MEDCPIM094SFRBCLE	**0.57**	**0.59**	**0.66**
LOANINV	1.14	1.16	1.39
LOANS	**0.94**	**0.98**	1.12
MCOILBRENTEU	1.12	1.22	1.17
GASREGM	**0.88**	1.06	1.18
POPTHM	1.19	1.23	1.27
IRLTLT01USM156N	1.02	1.16	1.21
SPCS20RSA	**0.99**	1.16	1.66
RMFSL	**0.83**	**0.88**	**0.93**
MSPNHSUS	1.03	1.17	1.44
APU000072610	1.00	1.06	1.16
TTLCONS	1.41	2.12	3.23
PCOPPUSDM	1.27	1.33	4.23
PI	1.31	2.68	11.74
ALTSALES	1.57	1.49	1.49
REAINTRATREARAT1YE	**0.98**	**0.95**	1.09
POLVOILUSDM	1.02	1.02	1.02
HTRUCKSSA	**0.95**	1.06	1.43
USGOVT	1.00	1.82	5.52
AUINSA	1.07	1.20	1.39
PWHEAMTUSDM	1.11	1.30	5.44
CES4348400001	2.32	4.38	9.22
TLAACBM027SBOG	1.27	1.63	2.38
PCEDG	1.53	1.75	2.26
UNDCONTSA	1.58	2.11	2.86
PNGASEUUSDM	1.05	1.01	**0.95**
TOTALSL	1.29	1.95	3.71
PALUMUSDM	1.11	1.14	1.17
POILBREUSDM	1.09	1.17	1.16
PNICKUSDM	1.10	1.23	6.89
USEPUINDXM	1.03	1.00	1.07
TRFVOLUSM227SFWA	1.53	1.89	2.43
PCES	1.78	2.44	3.73
CONSUMER	1.54	2.59	4.83
REVOLSL	1.19	1.81	2.78
DAUPSA	3.88	10.30	1.27
AMVPNO	**0.87**	1.15	1.42
BUSINV	**0.63**	**0.87**	1.59
CES4300000001	1.88	3.47	6.30
USFIRE	2.80	5.64	14.51
TRUCKD11	1.91	3.60	8.60
PCOALAUUSDM	1.04	**0.94**	**0.88**
PRAWMINDEXM	1.02	1.09	1.45
GASDESM	**0.88**	**0.98**	1.02
PBARLUSDM	**0.95**	**0.99**	1.50
PMAIZMTUSDM	**0.96**	1.00	1.30
PPOILUSDM	1.04	1.10	4.91

Variable	$T+1$	$T+2$	$T+4$
PCOTTINDUSDM	**0.93**	**0.97**	1.38
POILWTIUSDM	1.14	1.24	1.16
HQMCB10YRP	1.08	1.36	3.05
RETAILIMSA	**0.53**	**0.80**	1.89
MVMTD027MNFRBDAL	1.27	1.84	5.90
FORD	1.05	1.13	1.65
eff_tariff	1.00	1.00	1.01
GSPCI	1.24	1.41	2.08
IMPCH	1.14	1.44	2.72

Table 9: CFAVAR vs RW Ratios by Forecast Horizon

Variable	$T+1$	$T+2$	$T+4$
GEPUCURRENT	1.19	1.05	**0.96**
M1SL	1.39	1.21	1.22
M2SL	**0.81**	**0.94**	**0.92**
M1REAL	1.34	1.16	1.18
FEDFUNDS	**0.78**	**0.80**	**0.79**
USTRADE	**0.92**	**0.87**	**0.64**
CPIAUCSL	**0.72**	**0.76**	**0.54**
CPILFESL	**0.66**	**0.67**	**0.66**
CSUSHPINSA	**0.96**	**0.97**	1.00
PCE	**0.63**	**0.68**	**0.41**
BAA	1.28	1.23	1.03
CPALTT01USM661S	**0.72**	**0.76**	**0.55**
GS1	**0.82**	**0.78**	**0.76**
REAINTRATREARAT10Y	1.00	**0.96**	**0.88**
SAHMREALTIME	**0.74**	**0.79**	**0.74**
CUSR0000SETA02	**0.98**	**0.99**	**0.96**
CCLACBM027SBOG	1.46	1.43	1.10
UMCSENT	1.18	1.38	1.15
PCEPI	**0.73**	**0.74**	**0.62**
INDPRO	**0.00**	**0.00**	**0.00**
HOUST	**0.72**	**0.58**	**0.60**
DPSACBM027SBOG	**0.78**	**0.87**	**0.87**
MCOILWTICO	**0.90**	**0.88**	**0.73**
TOTALSA	**0.88**	**0.74**	**0.58**
MSACSR	**0.92**	**0.91**	**0.88**
CUSR0000SEHA	**0.61**	**0.59**	**0.58**
CUUR0000SETA01	**0.93**	**0.93**	**0.93**
CUUR0000SA0R	1.08	1.18	**0.92**
CUSR0000SAF11	**0.98**	**0.97**	**0.92**
CPIENGSL	**0.97**	1.11	**0.88**
CUSR0000SAM2	1.05	1.08	1.10
CHNCPIALLMINMEI	1.09	1.22	1.29
PPIACO	**0.74**	**0.76**	**0.71**
WPU0911	1.01	**0.98**	**0.97**
PCU325211325211	**0.90**	**0.95**	**0.95**
WPU101707	1.04	1.04	1.07
PCUOMFGOMFG	**0.84**	**0.86**	**0.75**
PCU325325	**0.74**	**0.78**	**0.76**
WPUSI012011	**0.94**	**0.94**	**0.93**
PCU311311	1.20	1.10	1.04
PCU325412325412	1.15	1.38	1.90
PCU483111483111	1.01	**0.98**	**0.86**
PPIIDC	**0.73**	**0.76**	**0.69**
WPU012	1.05	1.07	1.03
PCU482111482111	1.02	**0.95**	1.02

Variable	$T+1$	$T+2$	$T+4$
WPU0561	**0.86**	**0.92**	**0.74**
MPRIME	**0.80**	**0.77**	**0.77**
CURRCIR	1.00	1.14	1.07
EXCHUS	1.01	1.02	1.01
MEDCPIM094SFRBCLE	**0.64**	**0.63**	**0.61**
LOANINV	1.84	1.72	1.29
LOANS	1.71	1.43	1.04
MCOILBRENTEU	**0.89**	**0.87**	**0.72**
GASREGM	**0.95**	1.08	1.00
POPTHM	1.24	1.29	1.35
IRLTLT01USM156N	**0.87**	**0.89**	**0.79**
SPCS20RSA	**0.98**	**0.96**	**0.99**
RMFSL	1.05	1.01	**0.90**
MSPNHSUS	1.00	**0.96**	1.01
APU000072610	1.19	1.22	**0.94**
TTLCONS	1.22	1.20	**0.98**
PCOPPUSDM	1.28	1.36	1.55
PI	1.16	1.17	1.16
ALTSALES	**0.90**	**0.75**	**0.58**
REAINTRATREARAT1YE	1.01	**0.96**	**0.84**
POLVOILUSDM	1.02	1.03	1.03
HTRUCKSSA	**0.92**	**0.75**	**0.67**
USGOVT	**0.77**	**0.86**	**0.95**
AUINSA	1.00	1.03	1.14
PWHEAMTUSDM	1.11	1.13	1.11
CES4348400001	**0.91**	**0.81**	**0.53**
TLAACBM027SBOG	1.03	1.07	**0.84**
PCEDG	**0.73**	**0.70**	**0.70**
UNDCONTSA	1.48	1.39	1.21
PNGASEUUSDM	1.06	1.06	1.05
TOTALSL	1.03	1.04	**0.95**
PALUMUSDM	1.11	1.13	1.18
POILBREUSDM	**0.90**	**0.90**	**0.85**
PNICKUSDM	1.14	1.24	1.30
USEPUINDXM	1.42	1.00	**0.89**
TRFVOLUSM227SFWA	**0.70**	**0.83**	**0.72**
PCES	**0.63**	**0.76**	**0.63**
CONSUMER	1.42	1.49	1.25
REVOLSL	**0.95**	1.01	**0.89**
DAUPSA	3.65	3.96	1.03
AMVPNO	**0.44**	**0.46**	**0.47**
BUSINV	**0.54**	**0.54**	**0.61**
CES4300000001	**0.91**	**0.83**	**0.55**
USFIRE	1.21	1.12	**0.64**
TRUCKD11	**0.93**	**0.85**	**0.80**
PCOALAUUSDM	1.03	**0.94**	**0.91**
PRAWMINDEXM	1.10	1.18	1.25
GASDESM	**0.90**	**0.98**	1.00
PBARLUSDM	**0.95**	**0.99**	1.04
PMAIZMTUSDM	1.02	1.06	1.01
PPOILUSDM	1.14	1.19	1.18
PCOTTINDUSDM	**0.97**	1.02	1.06
POILWTIUSDM	**0.90**	**0.89**	**0.73**
HQMCB10YRP	1.36	1.30	1.00
RETAILIMSA	**0.51**	**0.57**	**0.64**
MVMTD027MNFRBDAL	**0.95**	**0.88**	**0.66**
FORD	1.00	1.00	1.05
eff_tariff	1.01	1.01	1.00
GSPCI	1.06	1.10	1.03
IMPCH	1.03	**0.99**	1.01

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