Estimating the Macroeconomic Impact of Industrial Shocks: a Supply Chain Risk Analysis

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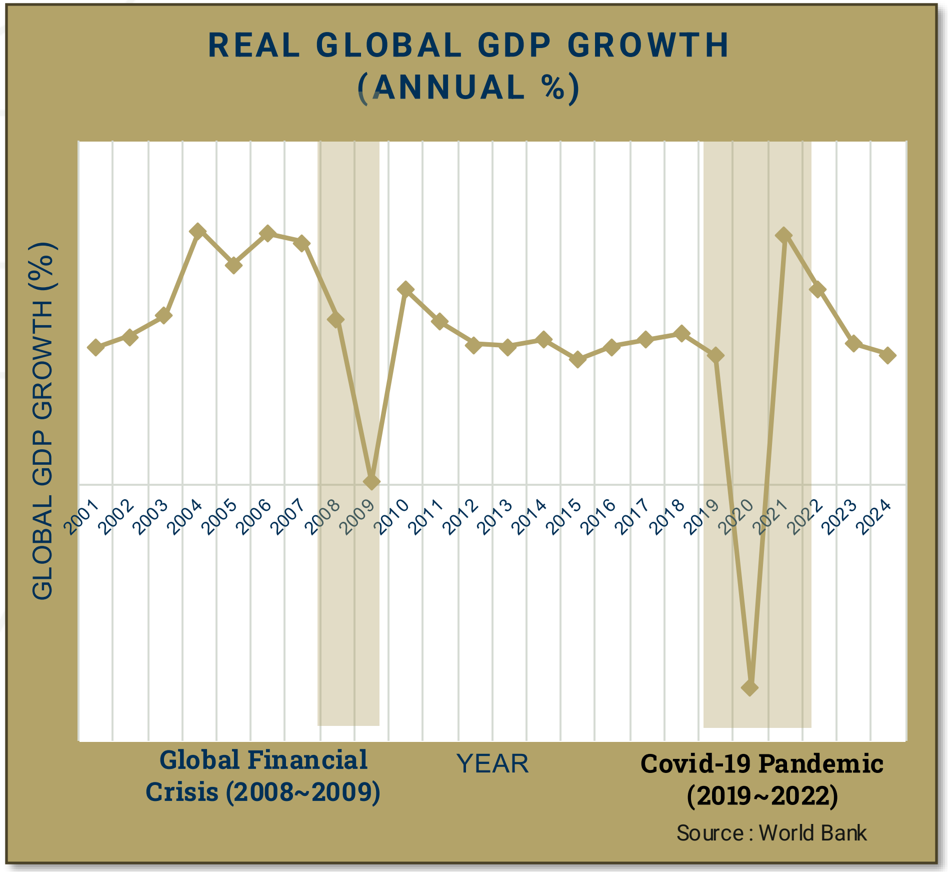
Why This Matters - Recent Supply Chain Crises



Annual Global GDP growth percentage

- Global crises (Pandemic, Subprime Crisis) had major impact on supply chains.

Major incidents

- **GM & Chrysler** (2009): Demand collapse + inventory misalignment → Bankrupt
- **Toyota & Ford** (2019~2022): Semiconductor chip shortages → Millions of vehicles not produced
- **Peloton** (2021~2022): Overestimated demand during Covid → Overproduction → inventory surge due to pandemic delivery delay → stock collapse (-90%)
- **Nike** (2022): Freight normalization + demand slowdown → $9B inventory glut (+44%)

Highlights how difficult it is for firms to anticipate how unexpected global crises propagate through freight, demand, inventory and production.

- *How fast will demand fall? Freight bottleneck ? Inventories spike ? Employment adjust?*

Why This Matters

- We need a **risk analysis tool** that quantifies how shocks propagate through the supply chain and supports planners in decision making.

- Traditional forecasts cannot predict sudden breaks in the economy (pandemic, bubble bursts, global strikes); we need **conditional forecasting**.

Core idea: Time series do not move alone; they are influenced by one another. By **imposing the path** on well-chosen variables, we can get better forecasts on the entire dataset!

Solution: Vector Auto-Regression (past & present values influence each other)

$$\boxed{\begin{pmatrix} x_t \\ y_t \end{pmatrix}} = \boxed{\begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{pmatrix} \begin{pmatrix} x_{t-1} \\ y_{t-1} \end{pmatrix}} + error_t$$

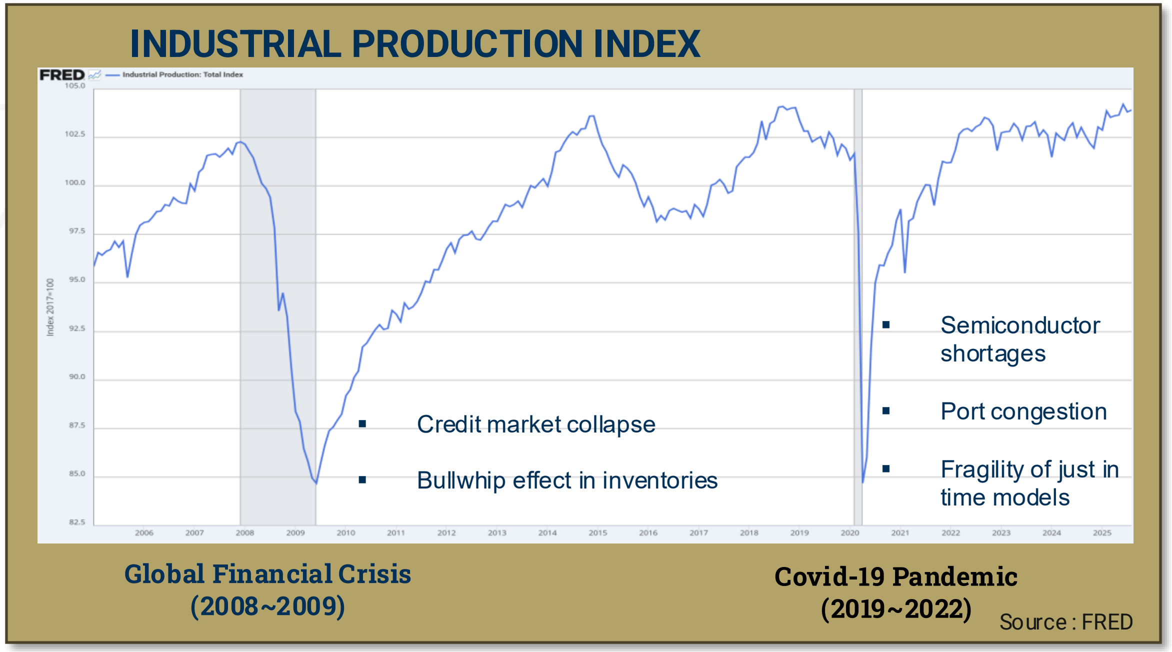
VAR(1) with two variables

$$\boxed{\mathbf{z}_t} = \boxed{A_1 \mathbf{z}_{t-1}} + \cdots + A_p \mathbf{z}_{t-p} + error_t$$

Generalized VAR(p)

Case Study – Modelling a Pandemic

- COVID-19: **largest & fastest macro disruption** in modern times.
- **Lockdown:** Created a dip in U.S. Industrial Production. This shock propagated through all the economy; influencing employment, inventories, sales, prices…



Industrial Production Index (IP)

- Output of the U.S. manufacturing, mining and utilities (electric and gas) sectors.
- Measures how much physical output the U.S. goods producing sector is generating.

➔ Widely used as a proxy for supply side activity in the industrial economy.

IP is a **great indicator to model the dip** in Supply Production shocks caused by a lockdown

By **conditioning on this variable**, we should be able to model the effects of a global pandemic.

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The Solution : Factor Augmented Vector Auto Regression

Core Idea:

- Compress hundreds of correlated macro variables into a few **latent factors** (F_t).
- These factors capture the common movements in the economy.
- Greatly reduces the dimensionality while retaining essential dynamics.

Mathematical Formulation:

- **FAVAR(1)** – 1 lag:

$$\boldsymbol{z}_t = \begin{pmatrix} F_{1,t} \\ F_{2,t} \\ F_{3,t} \\ IP_t \end{pmatrix} = A_1 \begin{pmatrix} F_{1,t-1} \\ F_{2,t-1} \\ F_{3,t-1} \\ IP_{t-1} \end{pmatrix} + error_t$$

- F_t : latent factors extracted through **Principal Component Analysis**.
- IP_t : Industrial Production at *t* (the variable we set the conditional path on)

100+ macroeconomic variables ⇒ 3 latent factors + Industrial Production Index

Stable estimation, interpretable structure, efficient forecasting !

Follow up question: what do these factors mean?

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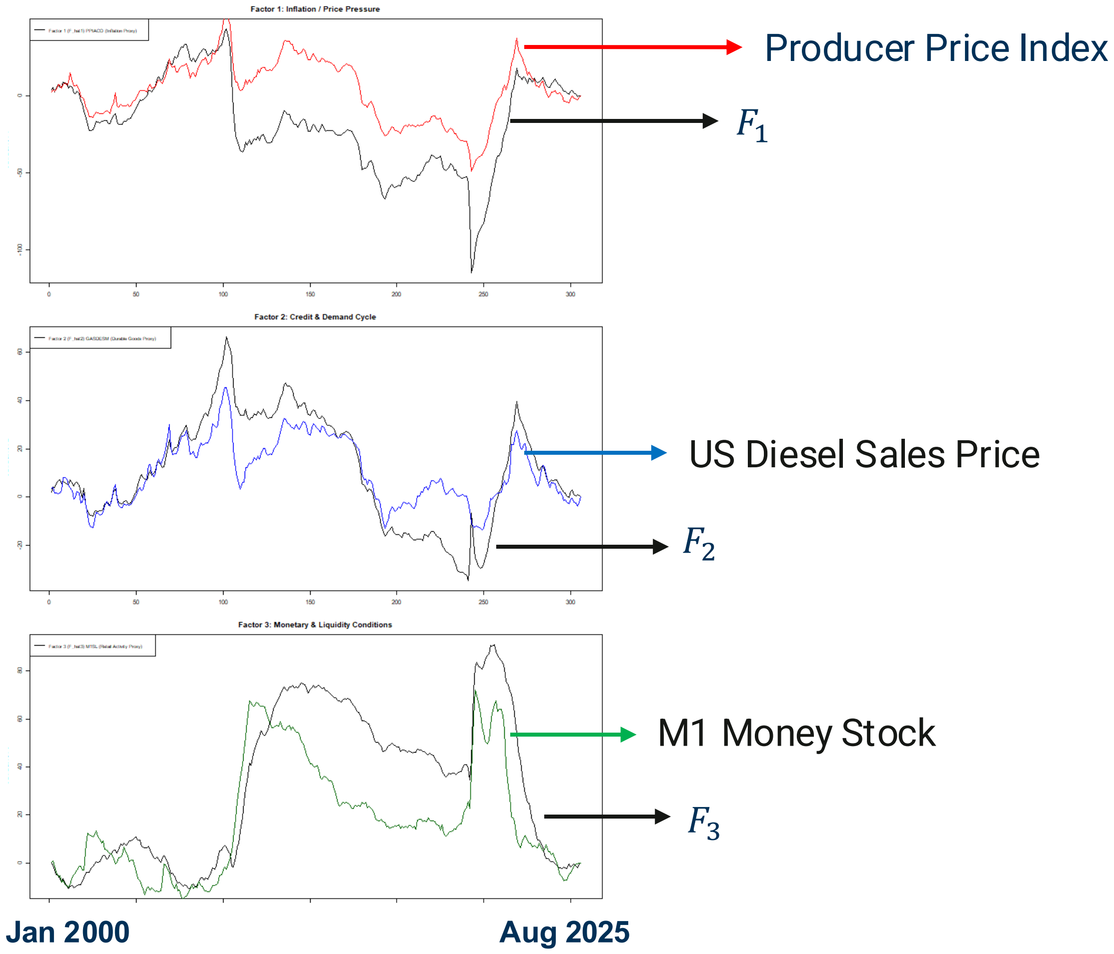
Economic Interpretation of the Three Latent Factors (F_t)

How does these factors compare to a few variables over time ?

Factor	
F_1	*Inflation & Cost Pressure* ✓ Tracks prices, energy costs, and production margins.
F_2	*Credit & Demand Cycle* ✓ Captures lending activity and cyclical demand.
F_3	*Monetary Policy & Liquidity* ✓ Reflects Fed policy stance and interest rates.

Factors over time along close correlated time series



These three factors explain + 65% of the variance of the entire dataset !

Conditional FAVAR Framework

FAVAR is a great candidate to extend on with a conditional forecast model !

✓ *Variable of interest =* IP_t

✓ *VAR framework = high interpretability*

✓ *Factor Analysis = covers a large panel of info.*

Model:

- We will be using a **state/space formulation** + **Kalman filtering** to impose a **conditional path** on IP_t.
- Assuming FAVAR(2): $z_t = A_1 z_{t-1} + A_2 z_{t-2} + error_t$
- State/Space reformulation:

$$\underbrace{\begin{pmatrix} z_t \\ z_{t-1} \end{pmatrix}}_{\alpha_t} = \underbrace{\begin{pmatrix} A_1 & A_2 \\ I & O \end{pmatrix}}_{T} \underbrace{\begin{pmatrix} z_{t-1} \\ z_{t-2} \end{pmatrix}}_{\alpha_{t-1}} + \underbrace{\begin{pmatrix} error_t \\ 0 \end{pmatrix}}_{\eta_t}$$

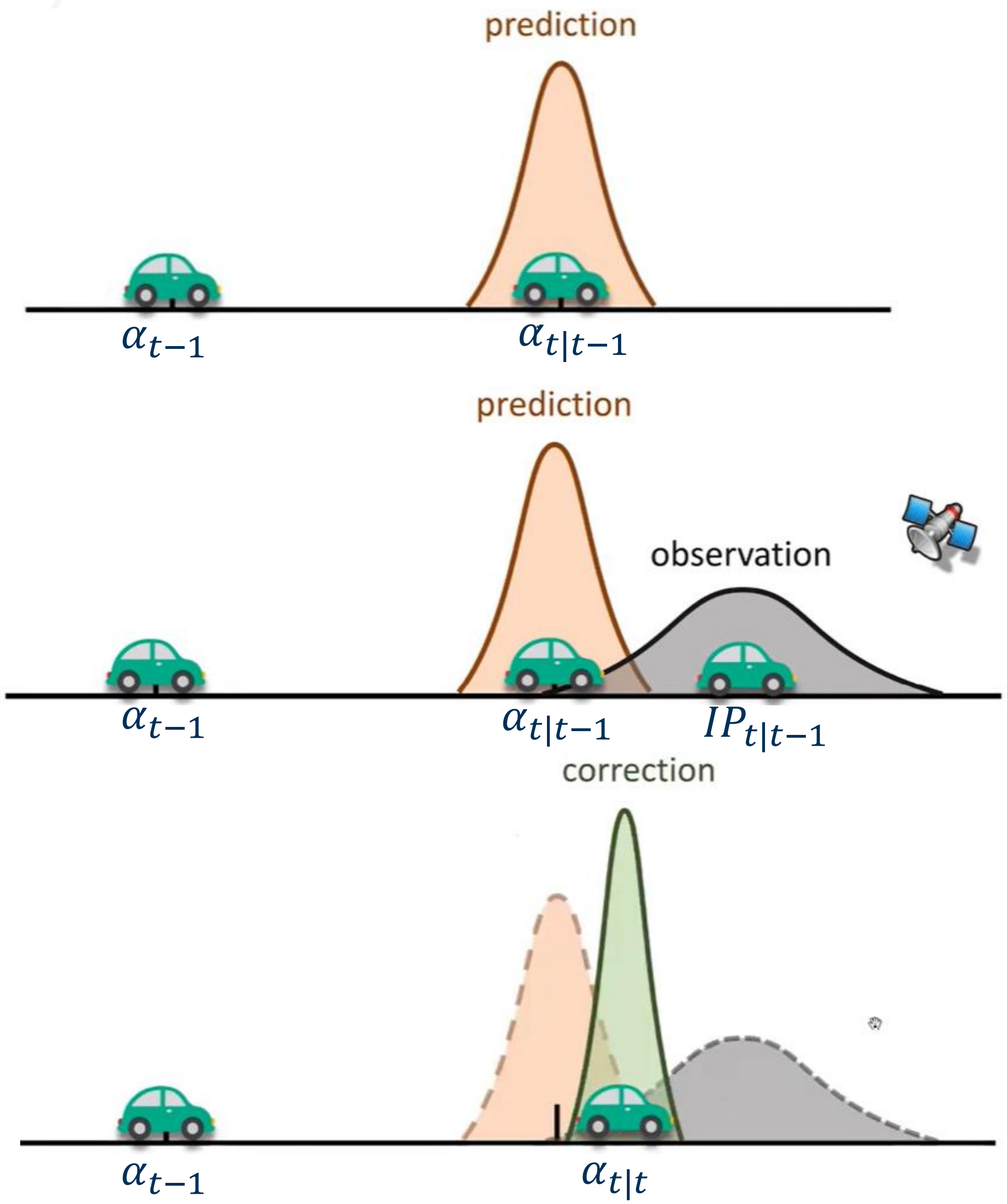
$$\alpha_t = T \alpha_{t-1} + \eta_t$$

It is a **Markov Process !**

⇒ we can apply a Kalman Filter

α_t: state vector

Kalman Filter – Analogy



Kalman Filtering for Conditional Forecasting is a 4-step iterative process.

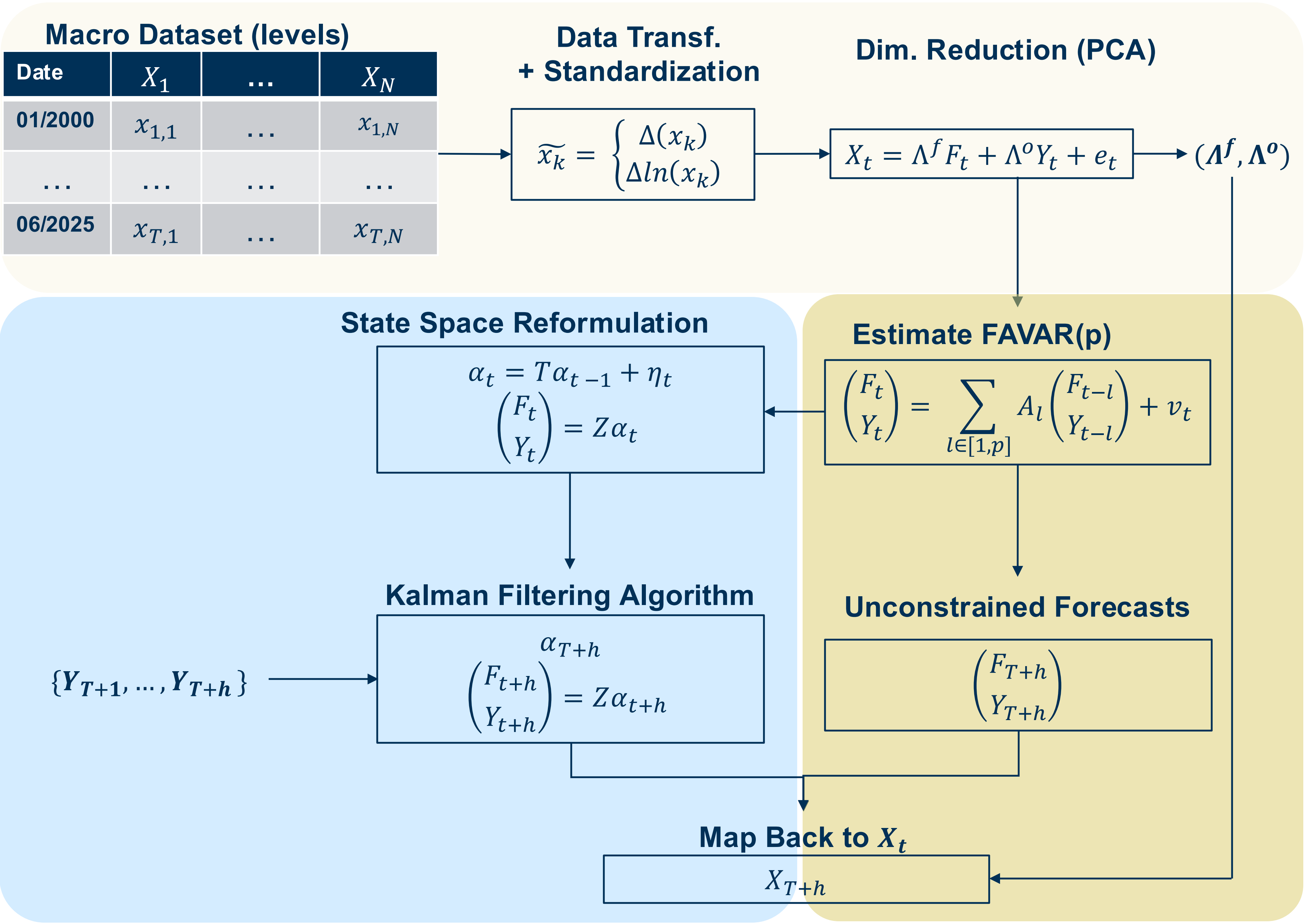
Step 1: Unconstrained pred. using Markov Eq.

Step 2: Consider the future value (“observable”).

Step 3: Estimate the corrected state (cond. Forecast)

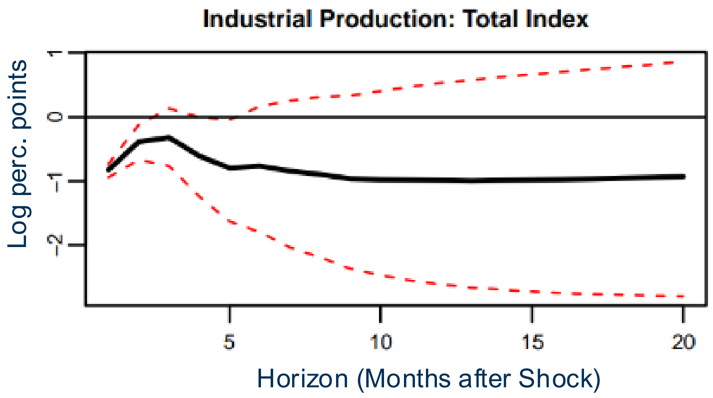
Roadmap

1. DATA PREPROCESSING
2. FAVAR
3. CFAVAR



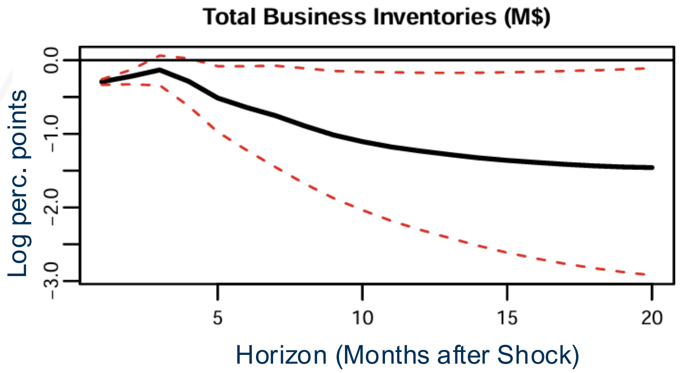
Sensitivity Analysis of the Model – Impulse Response (IRF)

- **Sensitivity testing** based on fluctuations of Industrial Production.
- Using the inverse PCA transformation ⇒ map back the effect to all the variables.
- IRFs are **not forecasts** ⇒ indicate how variables react on one another over time.
- Verifies the **consistency** of the FAVAR model.

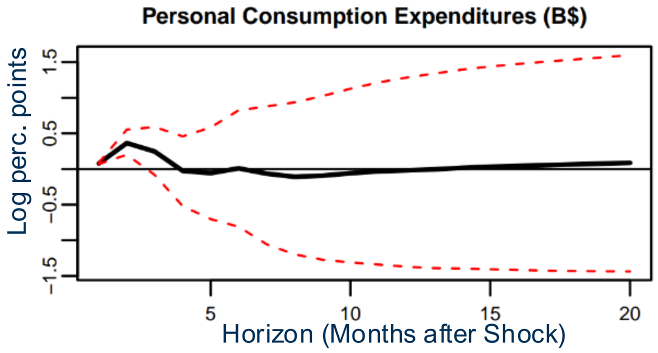


Median response

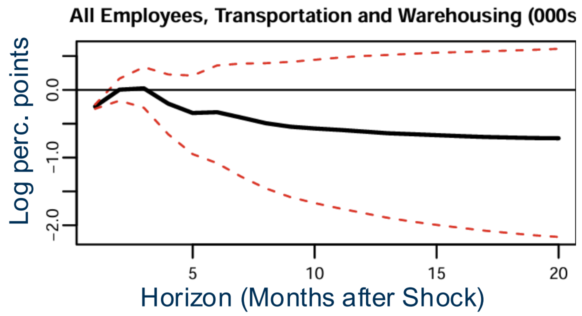
95% CI



- Decrease in production ($t = 0$) impacts **inventories negatively** over time.
- Happens when **production** does not follow **demand**.



- **Constant median PCE.**
- Industrial Production alone does **not impact individual spending.**
- Retail demand stays the same.



- Decrease of employees in Supply Chain sectors.
- Slow Supply Chain activity ⇒ **less need for workforce.**

Validation and Performance

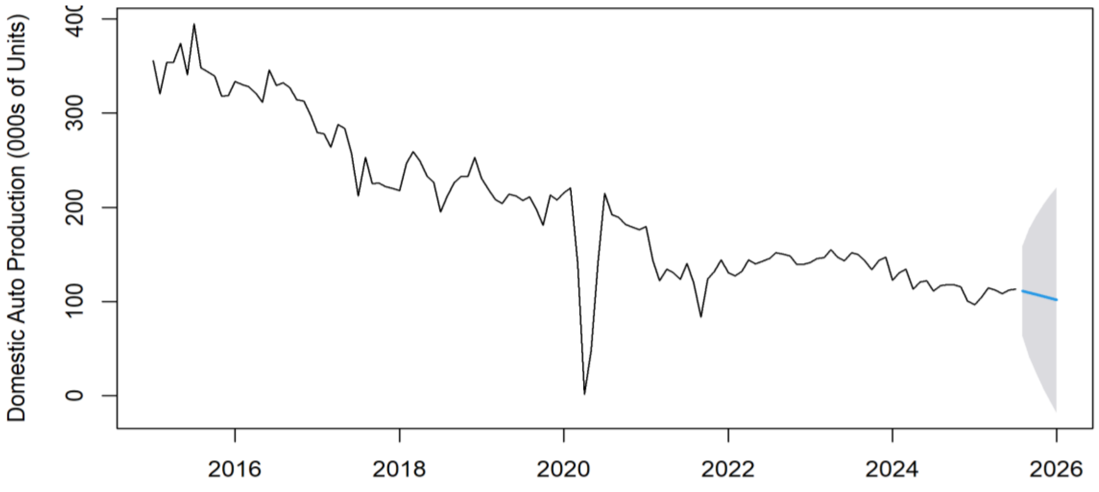
Motivation :

- Is the model **efficient** in a real-world scenario? Is it a **reliable** risk analytic tool?

- We will compare it to a **baseline** model: **Random Walk + Drift.**

$$\hat{X}^{RW}_{(t+h|t)} = X_t + h * \overline{\Delta X}$$

- In Macroeconomics, this model is **difficult to beat** on the long run !



RW + Drift 6 Month Forecast for Auto Production, 95% CI

Validation :

- Computing the **Mean Square Errors** (MSE) of both models (FAVAR and CFAVAR) to the RW.

- Evaluating MSE Ratios FAVAR/RW & CFAVAR/RW at different horizons.

Setup :

- 100 **rolling windows** from 2000~2025 (train = 200 obs, test = 100).

$$MSE^{(m)}_{j,h} = \frac{1}{100}\sum_{w=1}^{100}\left(X_{t_w+h} - \hat{X}_{t_w+h|t_w,j}\right)^2$$

Model m
Variable j
Horizon h

True value

Predicted value

Backtesting Results

- Run FAVAR and CFAVAR and RW models ⇒ compute MSE at different horizons ⇒ Estimate the Ratios
- Set the conditional path to be the **Industrial Production Index**

MSE Ratios for some selected variables

Model	FAVAR			CFAVAR		
Ratio	$\frac{MSE^{FAVAR}}{MSE^{RW}}$			$\frac{MSE^{CFAVAR}}{MSE^{RW}}$		
Horizon	**1 month**	**2 months**	**4 months**	**1month**	**2 months**	**4 months**
M2 Money Stock	**0.85**	1.42	3.43	**0.81**	**0.94**	**0.92**
Federal Funds Rates	1.29	1.59	2.16	**0.78**	**0.80**	**0.79**
CPI for All Urban Consumers	**0.68**	**0.88**	1.03	**0.72**	**0.76**	**0.54**
Industrial Production: Total Index	1.63	2.87	5.62	**0.00**	**0.00**	**0.00**
Total Vehicle Sales	1.56	1.49	1.50	**0.88**	**0.74**	**0.58**
…	…	…	…	…	…	…
Employees Truck Transportation	2.32	4.38	9.22	**0.91**	**0.81**	**0.53**
Business Inventories	**0.63**	**0.87**	1.59	**0.54**	**0.54**	**0.61**
Employees Trans.& Warehousing	1.88	3.47	6.30	**0.91**	**0.83**	**0.55**
Population	1.19	1.23	1.27	1.24	1.29	1.35

Unrestricted forecasting

Conditional forecasting

- If Ratio < 1: (Cond.)FAVAR better than RW
- Expected, we constrained this value
- Sometimes, even CFAVAR performance is worse than RW+ drift

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Validation Results

- Efficiency ratio ER : **Proportion of variables** for which the Model **outperforms** a Random Walk benchmark (MSE Ratio <1)

$$ER^{\frac{FAVAR}{RW}}$$

Forecast Horizon	Efficiency
1 month	39%
2 months	29%
4 months	14%

$$ER^{\frac{CFAVAR}{RW}}$$

Forecast Horizon	Efficiency
1 month	56%
2 months	57%
4 months	63%

Key Takeaways:

- Forecasting without conditionality is not performing well against benchmark.
- VAR relies on **recent dynamics**, RW uses the entire **historical average change**.

- Forecasting performance **improves drastically vs. RW** when imposing

⇒ Cond. forecasts : **reduce uncertainty** at the cost of **relying on assumptions**.

FAVAR's forecasting adv. deteriorates as horizon increases; it is the opposite for CFAVAR !

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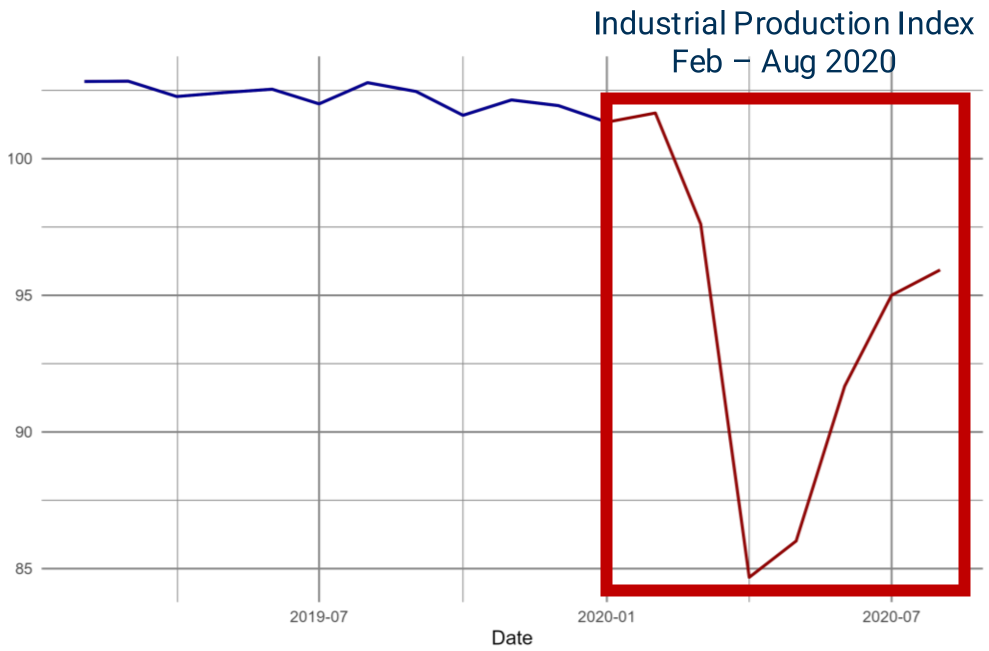
Case Study – Validating CFAVAR through Historical Crisis

Methodology:

- Impose the actual COVID-19 drop in Industrial Production in Feb-Aug 2020 (-10% drop in Feb 2020)
- Forecast horizon : 6 months
- Forecasted variables : Truck Traffic volume, Inventories, Employees for Transportation & Warehousing…



(1) CFAVAR (Conditional)

- Conditions on the imposed Industrial Production shock

$$\begin{pmatrix} F_t \\ IP_t \end{pmatrix} = A_1 \begin{pmatrix} F_{t-1} \\ IP_{t-1} \end{pmatrix} + v_t + Kalman\ Filtering$$

(2) Random Walk

- Baseline, unconditioned historical drift model

(3) Realized Path

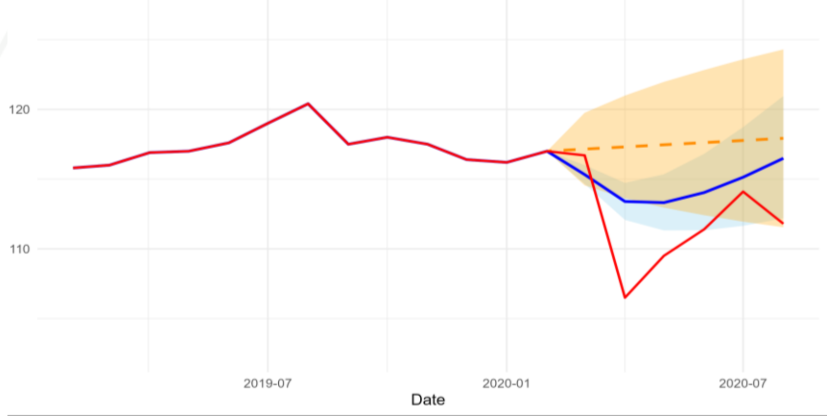
- Actual observed values during the crisis

What if Industrial Production shocks, How do other macroeconomic variables respond?

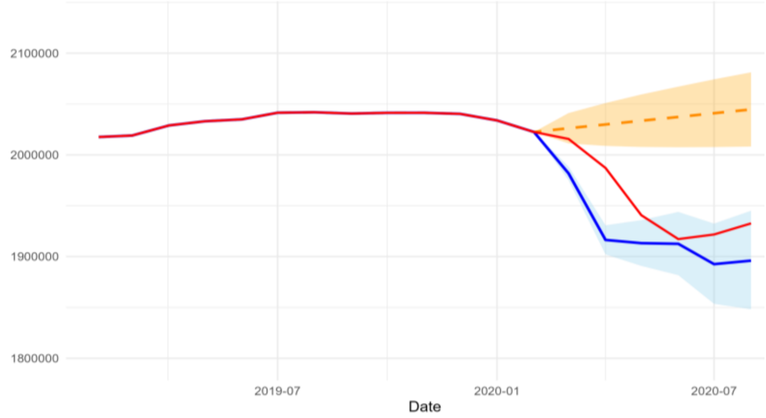
Case Study – Supply Chain Activity After COVID-19

Compared across how Freight, Inventories, and Employment metrics responded after COVID-19 crisis

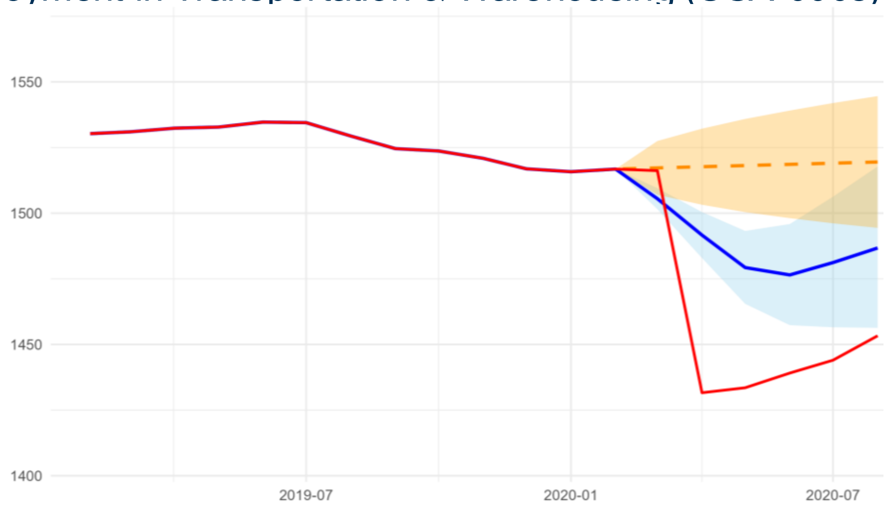
Truck Tonnage (USA-Million Tons)



Total Inventories (USA-Million $)



Employment in Transportation & Warehousing (USA-000s)



Realized path

Median Conditional Forecast

Median RW unconstrained forecast

95% CI Cond. Forecast

95% CI RW

Result: CFAVAR provides **tighter** and **more realistic** forecast ranges

➢ Great baseline, helping planners to production scheduling, labor & inventory planning

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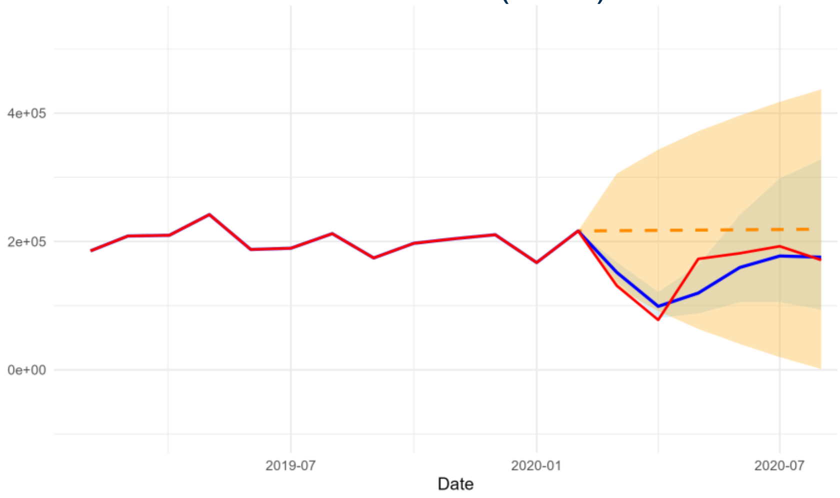
Case Study – Industrial Application (Ford)

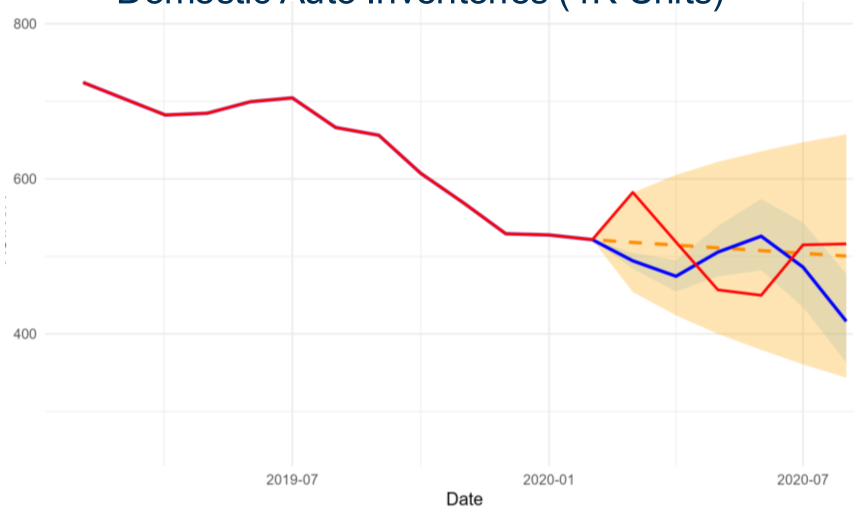
How firms can use CFAVAR to anticipate market responses after severe supply chain shocks

➢ How would Ford's Vehicle Sales & Inventories have responded to COVID-19?

Ford's vehicle sales (Units)



Domestic Auto Inventories (1K Units)



- Realized path
- Median Conditional Forecast
- Median RW unconstrained forecast
- 95% CI Cond. Forecast
- 95% CI RW

✓ CFAVAR allows us to impose a macro shock (e.g., Industrial Production drop) and trace how it propagates into Ford's internal situation (sales, shipments, orders, inventory..etc)

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Conclusion

Why CFAVAR Is a Better Tool for Supply Chain Risk Analysis

- Traditional forecasting assumes the future will behave like the past → fails when structural breaks occur (pandemics, tariffs, financial crises, labor strikes).
- Conditional forecasting lets us impose a scenario or shock path and observe how the rest of the system responds in a coherent way

→ CFAVAR is a better **risk-management tool**, it does not predict unexpected events but helps quantify "if this happens, then what?"

Conclusion

Flexibility and Limitations of CFAVAR

- Flexible and Not limited to Industrial Production
  - Industrial Production was one example shock, but CFAVAR can work with any macro driver (tariff , federal funds rate, oil shock..)

- Limitations
  - The results are **conditional** on the scenario you impose
    - If the imposed path is unrealistic or incorrect, the resulting forecast will also diverge

  - CFAVAR does not tell when unexpected shock will occur, only happens after you impose

Thank you