

Forecasting the Italian Industrial Production

Forecasting an economic variable in a peculiar period of time

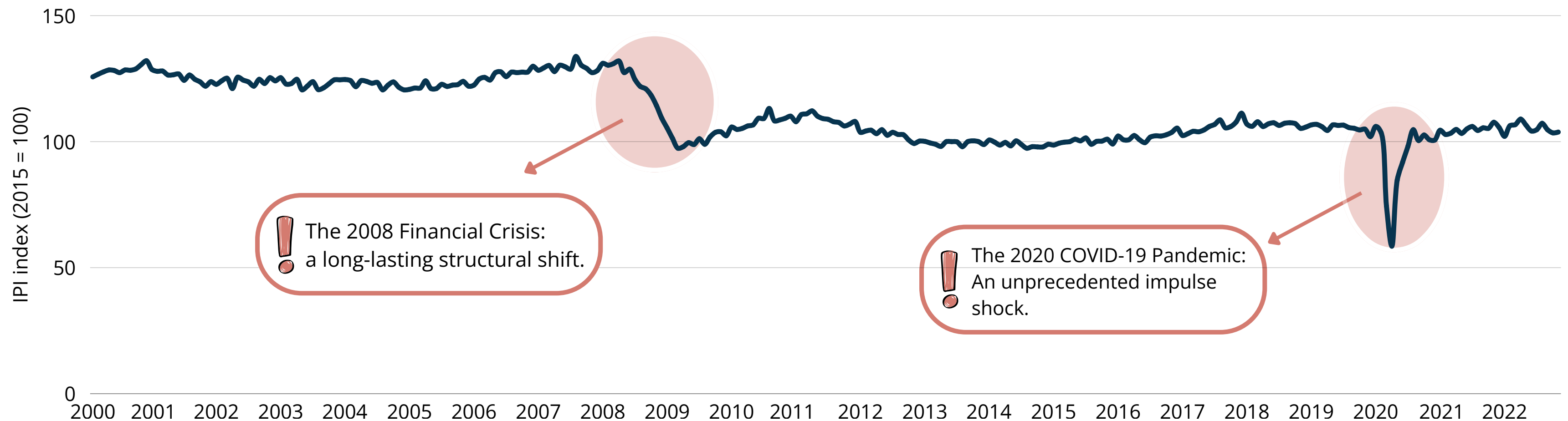
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The Data

The **Italian Industrial Production Index (IPI)** measures real activity in a predominantly manufacturing economy. The data displays significant **structural breaks complicating short-term forecasts** and **making it interesting** to analyze whether adding complexity to models can capture these unpredictable economic changes.



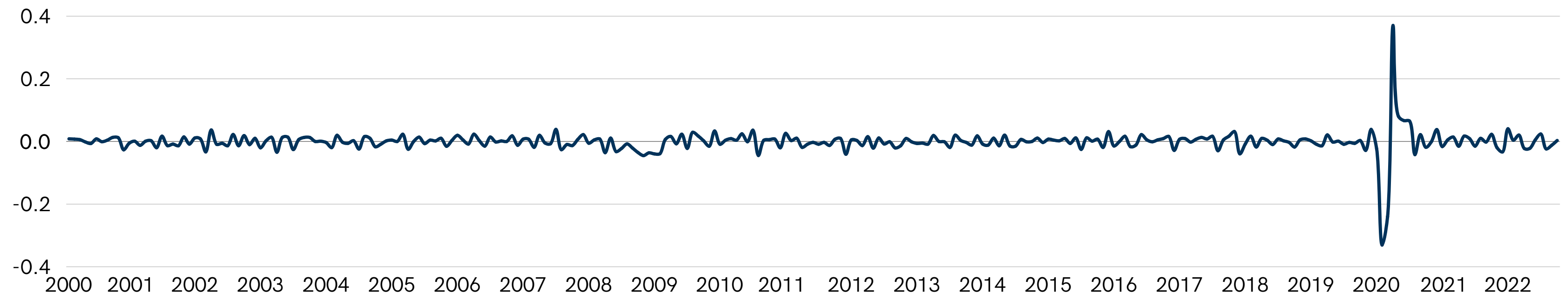
To refine the target variable estimate, additional predictors were added:

- **Core predictors** (FRED): Producer Price Index, unemployment rate, Brent crude oil price, Composite Leading Indicator (CLI).
- **Factor-model dataset** (Barigozzi.eu): panel of 31 monthly Euro-area indicators (labor market, prices, interest rates, industrial turnover, confidence indices, etc.) used to extract a common macro factor.

Data transformation

In order to apply specific time series forecasting model, we need to make our data stationary.

Example of data transformation: $\Delta \log(\text{IPI})$



Most series are non-stationary in levels, so transformed as:

- IPI, oil: log-difference
- Producer Price Index: monthly growth
- Unemployment: first difference
- Composite Leading Indicator: log-transformation

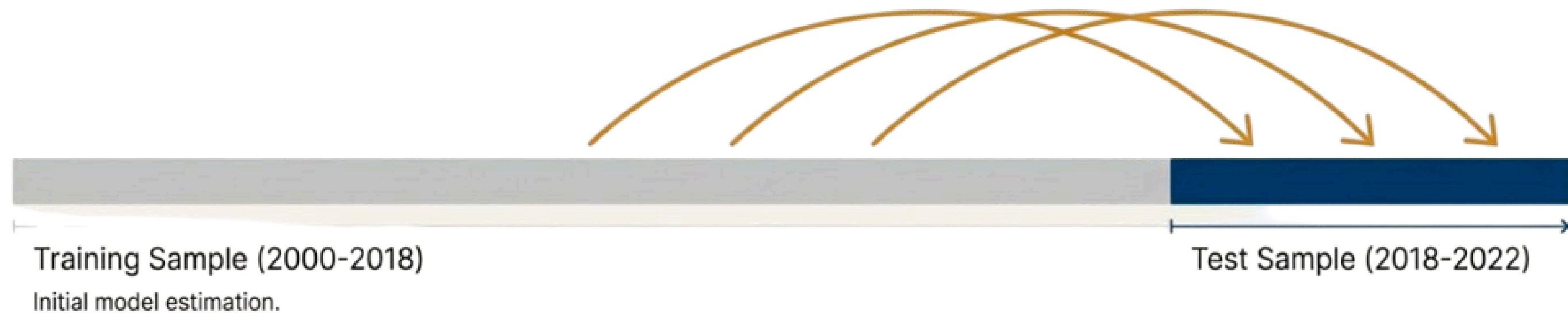


To better handle breaks

- Covid-19 impulse (temporary collapse & rebound in 2020)
- 2008 crisis shift (persistent level drop)

NB: ADF tests were used to support stationarity before and after transformation.

The Rules of the Evaluation: A Real-Time Simulation



Horizon

All models are evaluated exclusively on 1-step-ahead forecasts.

Framework

We use a recursive expanding-window scheme to mirror real-time forecasting.

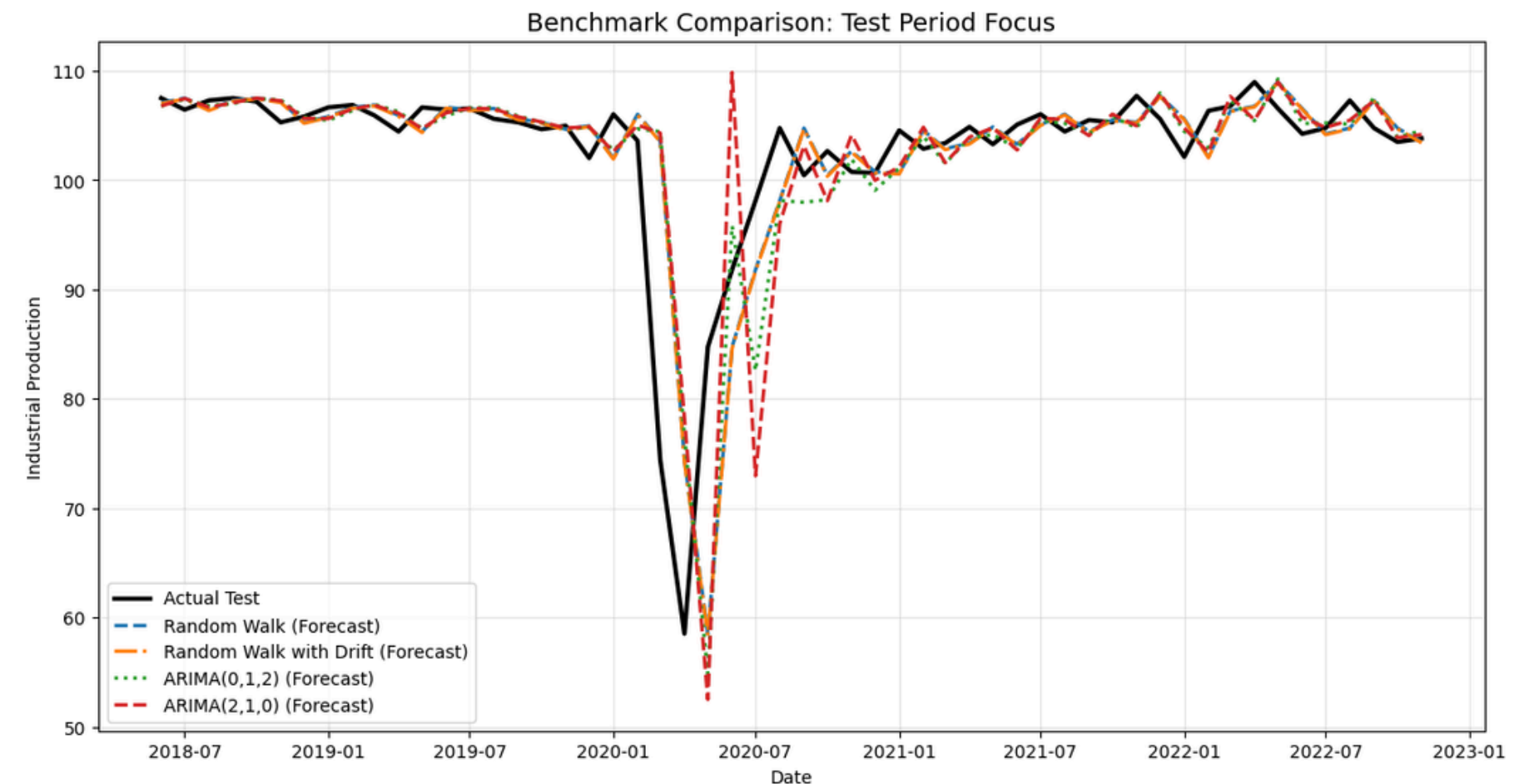
Evaluation

Accuracy is measured by Root Mean Squared Forecast Error (RMSE) and Mean Absolute Forecast Error (MAE)

Contender 1: Benchmark Models → RW

Univariate benchmark: we compared a **Random Walk** against **various ARIMA**:

- **ARIMA(0,1,2)** is the ARIMA chosen by the **AIC/BIC**. It succeeds in all diagnostic test.
- **Random Walk**: as expected it doesn't perform as well as ARIMA models in-sample (it doesn't pass the Ljung-Box test), but it performs better out of sample, possibly due to the peculiarity of our test set.

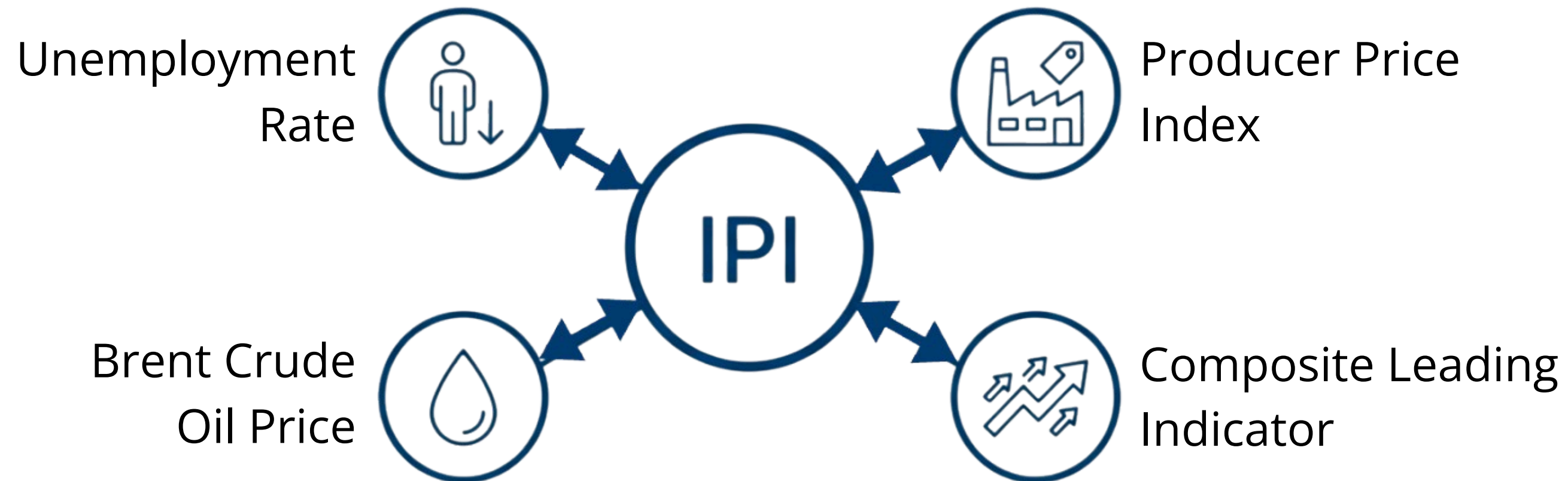


NB: Diagnostic tests include: t-test for zero mean, Ljung-Box up to lag 12 and stability tests.

Contender 2: VAR-X(1) Model

To examine whether other macro-economics variables help in the forecast the VAR-X model was estimated.

- The four variables were used as **endogenous** variables of IPI
 - → **Granger Test** confirmed the influence of IPI on most of them and vice versa.
- The model is augmented also with **dummy variables** (2008 and Covid Crisis) making part of the exogenous part (X)

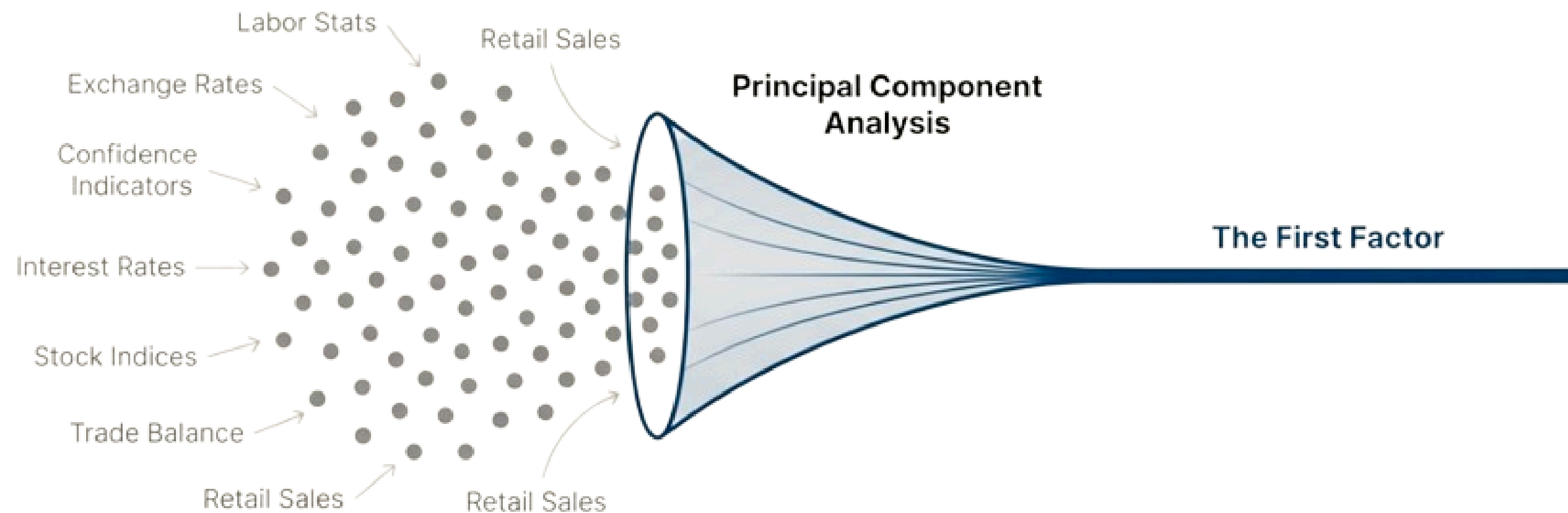


NB: AIC/BIC suggested the use 4 lags, but the VAR-X(1) also passed in-sample diagnostic tests and performed better oos.

Contender 3: Dynamic Factor VAR-X(1)

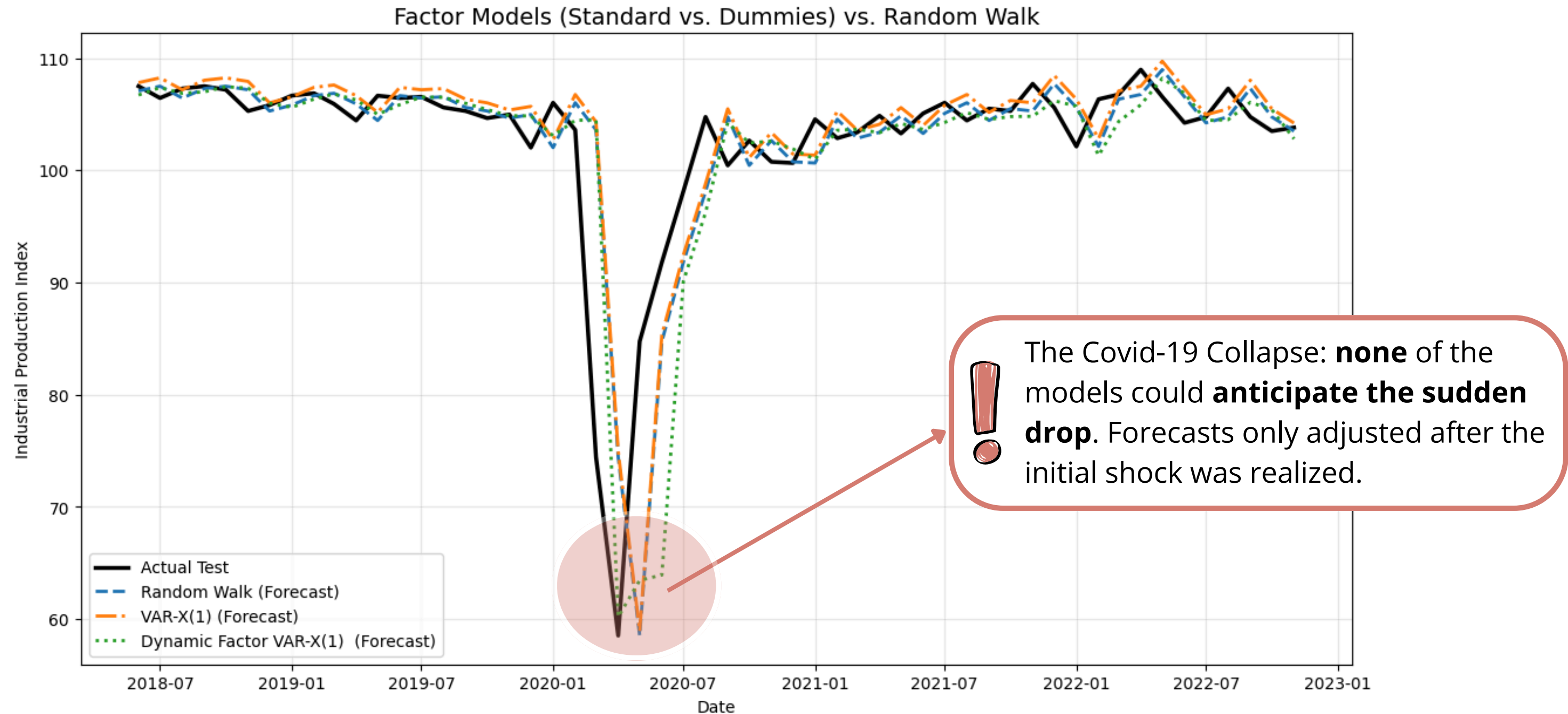
To incorporate a richer set of macroeconomic indicators without overloading the model, we build a dynamic factor model, applying principal component analysis (**PCA**) to obtain the **components**.

- Forecasting experiments indicate that **a single factor** offers the best performance. Therefore, we retain a common factor.
- The model passes both the t-test (confirming that the residual mean $\simeq 0$) and the Ljung-Box test.



NB: The version without dummies X was also modeled, but performed worse, indicating the relevance of our dummies.

Evaluation - Plot



The plot reveals that **differences between models are modest** compared to their common inability to predict an unprecedented shock.

The Covid-19 is, as predictable, a completely exogenous event that is not captured in anticipation by our regressors

Evaluation - Metrics

| Models | RMSFE | MAFE | | |
|-------------|--------|--------|----------------|---------------|
| Random Walk | 6.2359 | 3.0395 | RMSFE ratio | MAFE ratio |
| VAR-X(1) | 6.3049 | 3.1607 | 1.0111 | 1.0399 |
| FAVAR-X(1) | 6.7165 | 3.0884 | 1.0771 | 1.0161 |

The Random Walk benchmark achieves lowest error → Parsimonious theory

Adding richer macroeconomic information did not improve 1-step ahead forecast accuracy.

Interpretation of results and conclusions

Why did more complex model fail?



The Covid-19 extreme shock influences the test set too deeply.



Horizons too short, not enough time to recover and consider “normal times” data.

What could be done next?

- **Different forecast horizons** or a **longer** and **calmer** evaluation period could lead to a different model ranking.
- Future work could therefore consider **richer dynamic factor or machine-learning** approaches that better handle nonlinearities and structural breaks.