Machine Learning Methods for GDP Forecasting/Nowcasting

Cesar Zambrano[1]

[1]Department of Economics
New York University

Forecasting and Nowcasting GDP

Dynamic Factor Models (DFMs) remain the benchmark for GDP nowcasting and forecasting.

- Implemented by central banks: *GDPNow (Atlanta Fed), NY Fed Staff Nowcast, ECB.* Linzenich & Meunier (2024)
- Highly successful in forecasting macro variables. Stock & Watson (2002); Bai & Ng (2008); Stock & Watson (2011)
- Linear structure facilitates use of the Kalman Filter and forecast uncertainty analysis.

Recent research explores machine learning (ML) methods for macro forecasting.

Non-sparse ML approaches outperforms factor models in forecasting monthly inflation. Medeiros et al. (2021); Naghi, O'Neill & Zaharieva (2024)

However, evidence on whether ML improves GDP forecasting remains limited.

Contribution

This research evaluates how ML techniques can improve U.S. GDP forecasting using the FRED-MD dataset of monthly macroeconomic indicators.

Sum to efforts: Goulet-Coulombe (2024), Kant et al. (2022), Richardson et al. (2018)

Novelty: I follows the standard DFM Now-casting two-step approach:

- Estimate a 'bridge' equation that maps monthly macro variables to quarterly GDP.
- Estimate the monthly processes for macro variables.

Previous efforts have used a quarterly specification or estimated the direct map between monthly variables and quarterly GDP (static approach).

The benchmark used (for now) is a simple DFM.

Preliminary Results

Proposed pipeline:
LASSO on macro variables aggregated quarterly for the bridge equation.
XGBoost for prediction of the monthly variables.

Compared to a standard DFM benchmark.

- Accuracy gains[1] of 35.7% for Q1 2012 to Q1 2025
- Accuracy gains of 14.5% for Q1 2012 to Q4 2019 (Pre-Covid)

XGBoost performs much better than linear models in predicting monthly macro variables during Covid period.

- Industrial Production: 46.4% in accuracy gains.
- Real Personal Consumption Exp.: 28.8% in accuracy gains.

[1] Measured my RMSE

The Standard Nowcasting Pipeline

Use monthly macroeconomic variables x_t to predict quarterly GDP y_t (t = 3q).

$$y_{3q} = b(\mathbf{F}_{3q}) + \varepsilon^y_{3q}$$

where $\mathbf{F}_{t=3q} = \{\mathbf{f}_t, \mathbf{f}_{t-1}, \mathbf{f}_{t-2}, ..., \mathbf{f}_{t-j}\}$

$\mathbf{f}_t$ is the vector of r factors that drive each monthly variable:

$$x_{i,t} = \lambda \mathbf{f}_t + \varepsilon^i_t$$

which follows a law of motion:

$$\mathbf{f}_t = \boldsymbol{\theta}(\boldsymbol{L})\mathbf{f}_{t-1} + \boldsymbol{\varepsilon}^f_t$$

Forecasting: with information up to $3q - 3$, estimate $\{\hat{\mathbf{f}}_t, \hat{\mathbf{f}}_{t-1}, \hat{\mathbf{f}}_{t-2}\}$ to estimate y_{3q}.

Nowcasting: Incorporate new information from $3q - 3 < t \leq 3q$ into the estimate for y_{3q}.

The Atlanta Fed Nowcast

GDPNow uses a different variation of the factor model:

$$y_{3q} = b(\mathbf{X}_{3q}) + \varepsilon^{y}_{3q}$$

where $\mathbf{X}_{t=3q} = \{\mathbf{x}_t, \mathbf{x}_{t-1}, \mathbf{x}_{t-2}, ..., \mathbf{x}_{t-j}\}$
$\mathbf{x}_t$ is a vector of macroeconomic variables $x_{i,t}$, each following:

$$x_{i,t} = \boldsymbol{\lambda}\mathbf{f}_t + B(L)x_{i,t-1} + \varepsilon^{i}_{t}$$

And $\mathbf{f}_t$ follows a law of motion:

$$\mathbf{f}_t = \boldsymbol{\theta}(\boldsymbol{L})\mathbf{f}_{t-1} + \boldsymbol{\varepsilon}^{f}_{t}$$

Proposed ML Framework for Forecasting

Following the Specification:

$$y_{3q} = b(\mathbf{X}^y_{3q}) + \varepsilon^y_{3q}$$

And

$$x_{i,t+h} = g^i_h(\mathbf{X}^x_{t-1-h}) + \varepsilon^i_t$$

Estimate $b(X)$ and $g^i_h(X)$ using various ML methods:

- Variable Selection + Non-linearity.
- Less efficient in the presence of a highly linear and sparse true data-generating process.

Data and ML methods

Forecast: Quarterly GDP growth (annualized rate).

Data from the FRED-MS:

- Compiles 126 monthly macroeconomic series (macro indexes).
- Data used is from January 1960 to March 2025 (265 Q, 795 M).

About 10 macro series have missing data in which case the missing values are estimated (interpolation, extrapolation or using a highly correlated variable).

The variables are transformed following McCracken and Ng (2015).

For $\mathbf{X}^y$ and $\mathbf{X}^x$ I consider up to 4 quarters of lags.

For $\mathbf{X}^y$ I consider monthly (M) and quarterly (Q) data.

Training/Testing procedure

The Machine Learning methods considered for b(X) and g(X) (so far) are: LASSO, AdaLASSO, Ridge Regression (RR), Random Forest (RF), XGBoost (XGB),

Training sample: Q1-1960 to Q4 of 2011

Hyperparameter setting: 5 fold cross-validation.

Testing sample: Q1-2012 to Q1 of 2025

Criteria RSME

Results: Bridge Equation $b(X)$

Best $\hat{b}(X)$: from LASSO (Q) with 2 lags.

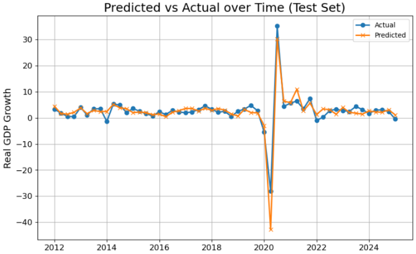
- RMSE: 2.62 (All test), 1.25 (Pre-Covid)

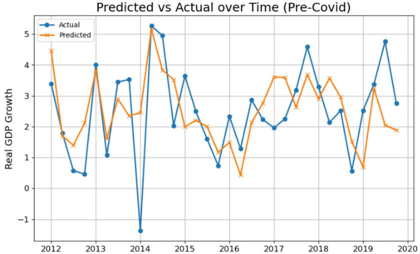
For reference, from the SPF[a]:

- Same Q: 2.31 (85:2023), 1.90 (85:1996)
- 1 Q ahead: 3.93 (85:2023), 2.01 (85:1996)

Comparison: RMSE S/RMSE LASSO (Q)

Specification:S	All	Pre-COVID
AdaLASSO (M)	0.92	0.94
LASSO (M)	0.89	0.91
AdaLASSO (Q)	0.86	0.98
Ridge (Q)	0.78	-
RF (M)	0.62	-
XGBoost (M)	-	-





[a]Federal Reserve Bank of Philadelphia, 2025

Results: Monthly Macro Variables Predictor $g_h(X)$

Best $\hat{g}_h(X)$ for the full test sample: XGBoost with 2 quarters of lag.

Diffusion index[2] is very competitive when considering Pre-Covid test sample

Comparison: *RMSE (XGBoost) / RMSE (Diffusion Index)*

Macro Variable	**h = 1**		**h = 2**		**h = 3**	
	All Sample	**Pre-COVID**	**All Sample**	**Pre-COVID**	**All Sample**	**Pre-COVID**
Real Personal Consumption Exp.	0.712	0.875	0.886	0.927	0.906	0.924
Industrial Production	0.536	0.952	0.656	0.911	0.891	0.951
Durable Consumer Goods	0.730	1.003	0.819	0.950	0.971	1.057
Business Equipment	0.688	1.167	0.776	1.095	1.001	1.077
Materials	0.601	0.969	0.659	0.890	0.838	0.918
Durable Materials	0.547	0.983	0.627	0.898	0.907	0.901
Residential Utilities	0.991	1.002	0.978	1.017	1.082	0.989
Civilians Unemployed - ($<$ 5 Weeks)	0.753	1.094	0.836	1.013	0.943	1.001
All Employees: Total Nonfarm Payroll	0.756	1.095	0.802	0.909	0.895	0.819
All Employees: Mining and Logging: Mining	1.015	1.123	0.989	1.119	1.061	1.165
All Employees: Durable goods	0.544	0.839	0.689	0.866	0.849	0.975
Avg Weekly Overtime Hours : Manufacturing	0.610	1.028	1.024	1.005	1.053	1.049
New Private Housing Permits, Northeast (SAAR)	0.908	1.041	0.921	1.015	1.028	0.941
S&P's Composite Common Stock: Dividend Yield	0.835	0.917	0.890	0.903	0.935	0.888
S&P's Composite Common Stock: Price-Earnings Ratio	0.892	0.906	0.926	0.910	0.980	0.896
Consumer Sentiment Index	0.791	0.999	0.784	1.047	1.102	1.026

[2] Number of factors (2) selected comparing Cumulative Explained Variance, Rate of Decay* (slows down) and Bai & Ng (2002) information criteria.

Results: Overall Forecast of $q + 1$

RMSE: 3.882 (All test), 1.352 (Pre-Covid)

For reference, from the SPF:

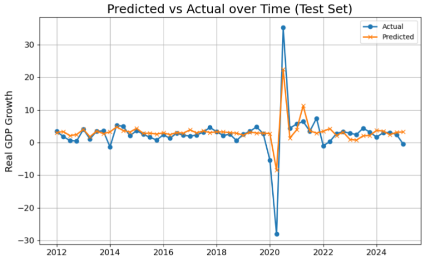
- Same Q: 2.31 (85:2023), 1.90 (85:1996)
- 1 Q ahead: 3.93 (85:2023), 2.01 (85:1996)

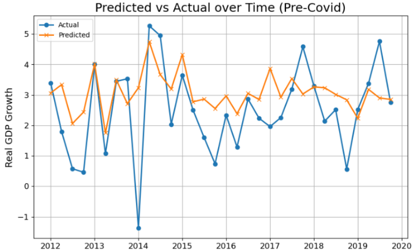
Simple DFM Benchmark:

- 7 factors (PCA). Stock and Watson (2011)
- 2 quarters of lags.
- RMSE: 5.948 (All test), 1.582 (Pre-Covid)

RMSE (Proposed) / RMSE (DFM Benchamrk):

- 0.653 (All test), 0.855 (Pre-Covid)





Gains from using XGBoosT

Second Benchmark: Keep LASSO (Q) $\hat{b}(X)$.

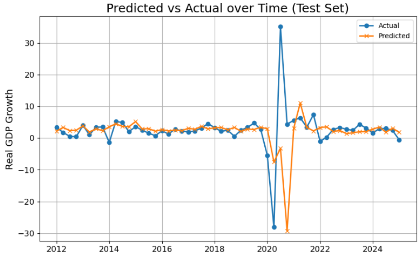
Replace XGBoost $g_h^i(X)$ by Diffusion index.

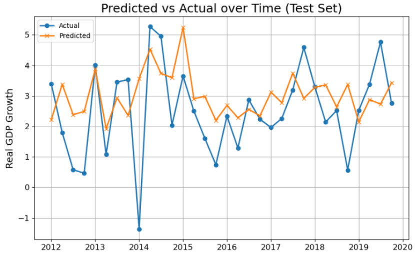
RMSE: 7.866 (Full Test), 1.474 (Pre Covid)

RMSE (Proposed) / RMSE (DFM Benchamrk):

- 0.500 (All test), 0.917 (Pre-Covid)

Models based on linear factors do poorly during Covid period!





Next Steps

Set up a better model benchmark.

- Better methods for estimating factors (EM) .

Consider new methods:

- Macroeconomic Random Forest. Coulombe (2024).
- Autoencoder + Regularization (for non-linear factors)

Work on the Now-casting problem:

- Consider $g^S_{i,h}(X(S))$.
- Method's alternative to handle missing data (e.g. Surrogate splits)

The Costs of Fiscal Uncertainty

Sovereign Debt Crisis and Real Activity

What is the connection between sovereign debt crisis and real activity?

Periods of crisis are market by acute decrease in real activity.

Explanations:

- Debt crisis affects financial intermediation (Balance sheet channel).
- Debt crisis affects firms access to imported inputs (working capital).

Real activity displays a *V-shaped* dynamic around the default event.

- Recovery is fast after default!

My two theories:

- Default time is endogenous.
- Default has the benefit of resolving uncertainty (this project).

Motivation

This project: Debt crisis are periods of high uncertainty.

- Who will bear the cost? Will the government default? Raise taxes/ Lower transfers? Cut expenditures?

What is the potential role of (distributional) uncertainty in driving down output during periods of fiscal crisis?

- Can it account for the sharp contraction in GDP and a surge in sovereign risk premia.
- Can the resolution of uncertainty explain the fast re-bounce?
- Does gains from revolving uncertainty explain concenter-cyclical fiscal consolidation.
- How much can it affect growth and the sovereign spread when the debt trajectory is *currently* stable.
- How can it shape the correlation between corporate and soverign risk premia?

Set Up

Two Agents: Home Entrepreneurs and Foreign Bankers.

Preferences: Aversion to ambiguity

Simple Production: $Y_t = A_t K_t$, with A_t potentially stochastic.

Segmented financial markets: (Key to uncertainty)

One period government bonds placed in the global financial market.

$$R_t = R^* + \text{default premium}(t)$$

Foreigners cannot invest in K.

Citizens cannot borrow money from abroad.

Return on K $> R^*$ - so domestic agent will not demand gov. bonds.

Set Up

The economy inherits:

- A tax rate on income: $\tau_t = \bar{\tau}$
- A government expenditure fraction of GDP: $g_t^e(s) = \bar{g}^e(s)$
- A government debt level fraction of GDP: $\bar{b}$

government budget (as share of GDP) is:

$$b_{t+1} = \frac{R_t b_t + g_t^e - \tau_t}{g_{t,t+1}^Y}$$

$g_{t,t+1}^Y = g_{t,t+1}^A g_{t,t+1}^K = \frac{A_{t+1} K_{t+1}}{A_t K_t}$

Unsustainable Government Budget

At the initial state, with no shock to A, budget is sustainable:

$$\bar{b} = \frac{R\bar{b} + g^e - \bar{\tau}}{g_Y}$$

At $\bar{t}$, a negative shock to A, or a government expenditure shock put the debt into an unsustainable trajectory: $b_{\bar{t}} < b_{\bar{t}+1} < b_{\bar{t}+2} < ...$

At stochastic time $T > \bar{t}$ after the initial shock, the government will address the situation.

Two options:

- Tax sequence/Debt deflation plan $(\{\tau_t\}, \{b_t\})$ makes debt sustainable.
- Partial default, back to sustainable debt levels.

Fiscal Consolidation Government

Committed to repaying debt:

$$R_t = R^*$$

Debt deflation plan:

$$b_{t+1} = \frac{\rho(b_t - b^*) + b^*}{g^A_{t,t+1}}$$

Where b^* is the sustainable debt level under $(\bar{\tau}, \bar{g}^e, R^*)$

Associated with the debt deflation plan is a tax plan:

$$\tau_t = R^* b_t + g^e_t - [\rho(b_t - b^*) + b^*] g^K_{t,t+1}$$

Since τ_t affects growth: $g^K_{t,t+1} = g^K(b_t, A_t)$

Default Government

Committed to the tax rate: $r_t = \bar{\tau}$

In this case: $g^K_{t,t+1} = \bar{g_K} \Rightarrow g^Y_{t,t+1} = \bar{g_K} g^A_{t,t+1}$ But Interest rates is:

$$R_t = R^* + \text{default premium}(t)$$

Pricing equation:

$$R^* = \mathbf{R_t} P[T \neq t+1] + \frac{b^D}{b_t} P[T = t+1]$$

Where b^D is the sustainable debt level under $(\bar{\tau}, \bar{g}^e, A_t)$

Since b_t affects R_t: $R_t = R(b_t, A_t)$

Three Economies

Committed to repayment:

- $R_t = R^*$
- $g^K_{t,t+1} = g^K(b_t, A_t) < \bar{g}^K$

Committed to default:

- $R_t = R(b_t, A_t) > R^*$
- $g^K_{t,t+1} = \bar{g}^K$

Government whose type is uncertain:

- $R_t = R(b_t, A_t) > R^*$
- $g^K_{t,t+1} = g^K(b_t, A_t) < \bar{g}^K$

Cost of Uncertainty

After a negative shock:

$$\uparrow b_t \Rightarrow \quad \uparrow R(b_t, A_t) \text{ and } \downarrow g^K(b_t, A_t) \Rightarrow \quad \uparrow b_t ...$$

Relative to a government committed to tax adjustment:

- b_t growths faster because of default premium
- $g^K_{t,t+1}$ decreases more due to higher accumulation of debt
- Both effects reinforce each other

In the steady state with uncertainty:

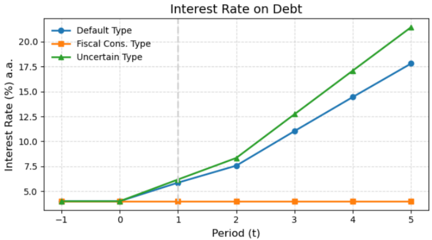
- Higher levels of R_t, lower levels of sustainable b^*
- Lower levels of $g^K_{t,t+1}$

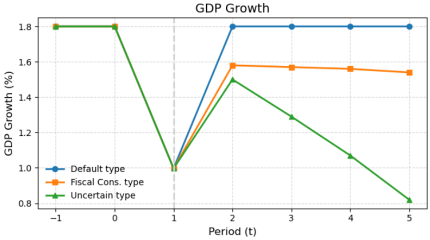
How sizable can be these effect?

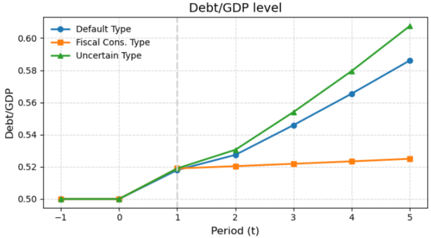
A Simple Exercise

$U(C_t) = \log(C_t)$
$A = 0.22$
$\beta = 0.95$
$R^* = 1.04$
$\bar{g}_e = 0.30$
$\bar{b} = 0.5 \Rightarrow \bar{\tau} \approx 0.311, g_Y \approx 1.0181$

At t = 1, 'MIT shock' reduces growth.







Steady State With Latent Uncertainty

Assume now that A_t is stochastic with $A_t \in \{A_H, A_L\}$.

A_t follows a 2x2 Markov Chain. For Fiscal Consolidation Government: $\tau = \tau(b, A)$

From the Euler Equation:

$$1 = \beta E\Big[\frac{1}{g_C(b, A)}(1 - \delta + A'(1 - \tau(b', A')))\Big]$$

With

$$g_C(b, A) = g_K(b, A)\frac{[1 - \delta + A'(1 - \tau(b', A'))] - g_K(b', A')}{[1 - \delta + A(1 - \tau(b, A))] - g_K(b, A)}$$

A Neural Network is used to find: $g_K(b, A)$