Macroeconomic Predictions using Payments Data and Machine Learning*

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August 22, 2023 (paper-link)

Bank OF Finland's 21st Simulator Seminar, Helsinki

*The opinions here are of the authors and do not necessarily reflect the ones of the Bank of Canada

Payments – economic pulse of a nation

The transaction volume of UPI – India's instant payment system declined by about 20% compared to its normal flow during the final minutes of a recent cricket match between India and Pakistan (source)

The **FedNow** just launched in US and the **RTR** is currently being developed in Canada

Motivation

Macroeconomic Prediction:

- **Delay**: official estimates are released with a substantial lag
- **Uncertainty**: undergo multiple revisions sometime after years
- **Crisis**: nonlinear impacts and unconventional policies

Payments Data & Machine Learning:

- **Timely & Precise**: available immediately, no measurement or sampling error
- **High-frequency & Broad**: daily aggregates, 15+ years, 20+ streams
- **Handle Big Data**: non-traditional, high-frequency, wide and large
- **Nonlinearity**: flexible in capturing nonlinear relationships

Objective

Perform a comprehensive assessment of the usefulness of payments data for macroeconomic predictions—with and without machine learning:

- Which (retail, wholesale), when (normal, crisis), and why (timeliness, variety)?
- Does machine learning (ML) add additional value (use of the shelf models)

Address the associated challenges in using such models for policy us:

- Shapley value-based approach to interpret ML model predictions
- Improved cross-validation strategy to alleviate the overfitting

Literature

Payments data for macroeconomic prediction: Galbraith & Tkacz (2018), Aprigliano et al. (2019), Chapman and Desai (2020)

$\rightarrow$ We use comprehensive payments data from retails and wholesale payments systems

Machine learning for macroeconomic prediction: Richardson et al. (2020), Maehashi and Shintani (2020), Coulombe et al. (2020), Babii et al. (2021)

$\rightarrow$ We test variety of ML models, both parametric and non-parametric

ML interpretability and overfitting: Lundberg et al. (2017), Buckmann et al. (2021), Babii et al. (2021), Bergmeir and Benitez (2012)

$\rightarrow$ Use new tools to address associated challenges

Results Preview

Timeliness of payments data and nonlinear ML models can help lower prediction errors significantly. 35-40% reduction in RMSE for predicting GDP, retail and wholesale sales

- **Payments** data with factor model help improve prediction accuracy up to 25%
- **Nonlinear** machine learning can help further improve accuracy up to 18%
- Payments data add more value at **nowcasting** horizon
- **Retail** payments data is more useful than data from wholesale system
- Usefulness of payments data surges during **crisis periods**
- Proposed cross-validation and interoperability tools can help improve effectiveness of these models for **policy use**—up to certain extent

Outline

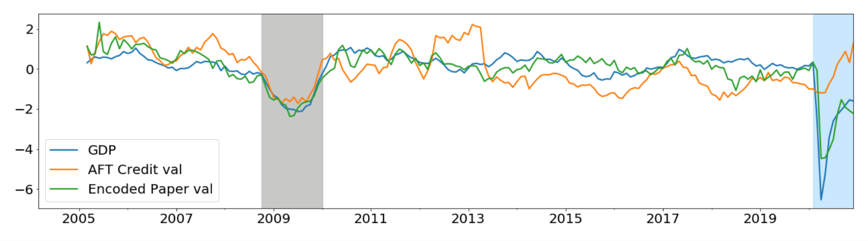
Data

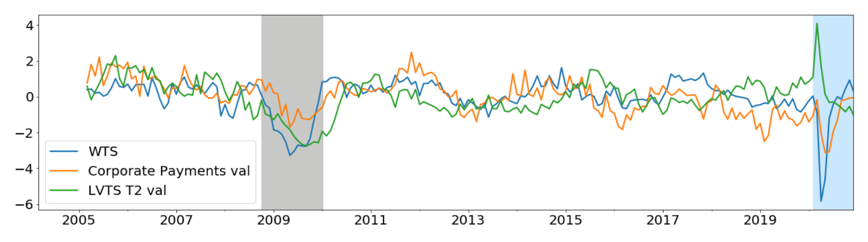
Canadian ACSS and LVTS Data

Stream	Short Description
AFT Credit	Direct Deposit: payroll, account transfers, social security
AFT Debit	Pre-authorized debit (PAD): bills, mortgages, utility
Encoded Paper	Paper bills: cheques, bank drafts, paper PAD, etc.
Shared ABM	Debit card payments to withdraw cash at ABM
POS Payments	Point of sale (POS) payments using debit card
Corporate Payments	Exchange of Corporate-to-Corporate and bill payments
Allstream	It is the sum of all payments streams settled in the ACSS
LVTS-T1	Time critical payments and payments to Bank of Canada
LVTS-T2	Security settlement, foreign exchange and other obligations

Automated clearing settlement system (ACSS) and the large-value transfer system (LVTS)

Payments Data for Prediction





Standardization year-over-year growth comparisons of monthly targets and payments streams

Methodology

Models

Dynamic Factor Model (DFM): Captures dynamics of large set of predictors into small number of latent factors

$$X_t = \Lambda f_t + \epsilon_t,$$
$$f_t = A_1 f_{t-1} + \cdots + A_p f_{t-p} + u_t$$

Gradient Boosting Regression (GBR): Sequence of small trees are built on a repeatedly modified training dataset

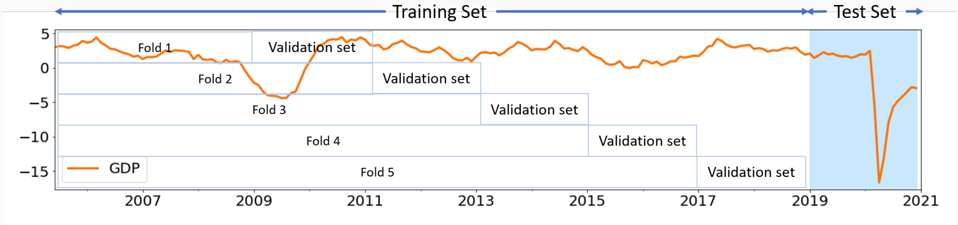
$$\hat{y}_i = \sum_{m=1}^{M} h_m(x_i)$$

Elastic Net, Support Vector Machines, Neural Network, and Random Forest

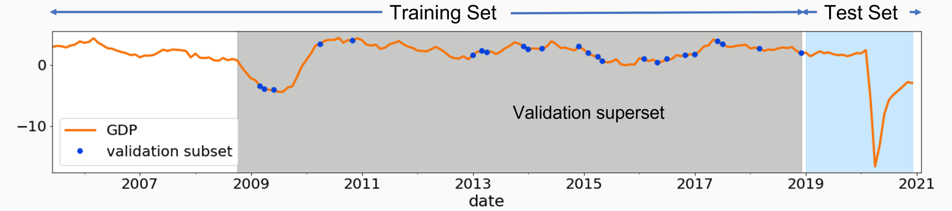
Overfitting

K-fold Cross-validation: Traditional vs Randomized Expanding Window

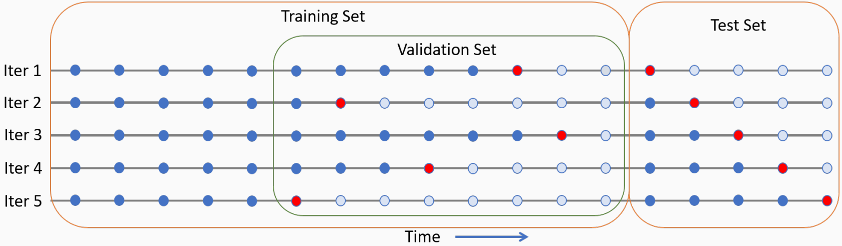
Standard approach for time-series:



Proposed approach for macroeconomic time series:



Randomized Expanding Window



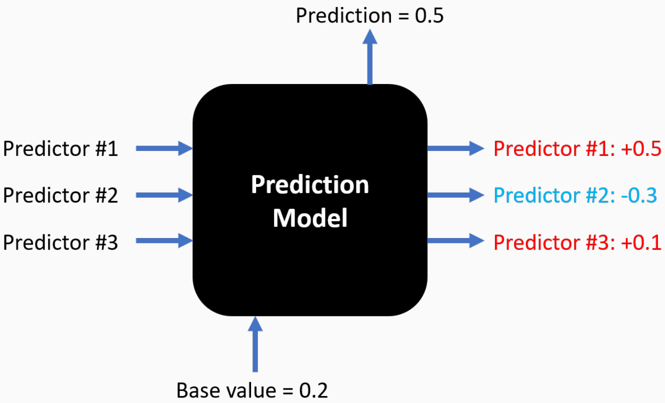
Advantages & Disadvantages:

- Distribution of each validation set is similar to the test set
- Help avoid breaking the order of data (autocorrelation)
- Could sample many validation sets (no constrains)
- Some observations may get selected more than once, and some may never get selected in the validation set (theoretical and empirical analysis needed)

Interpretability

Shapley Values: SHAP[1]

Example: Consider nowcasting is a "game" then the Shapley values can be used to fairly distribute the *payout* (= the prediction) among the *players* (= the predictors)



[1] Lundberg et al. (2017). SHAP: A unified approach to interpreting model predictions.

SHAP: Advantages & Disadvantages

Advantages:

- Foundations in game theory
- Model independent approach
- Local and global interpretation

Disadvantages:

- Computationally expensive with increasing number of predictors
- Parametric models suffer from collinearity in the predictors
- No optimal statistical criteria and asymptotics yet

Results

Case Specifications

Prediction horizons ($t, t+1, t+2$) are based on payments data availability t

E.g.: To predict May's GDP growth rates on June 1^{st}, i.e., at $t+1$, we use **payments data** for May (at t), and other latest available macro indicators:

- Base case (benchmark): OLS (5 predictor)[2]

$$\widehat{GDP}_{t+1} = \ \mathcal{F}(GDP_{t-2},\ CPI_{t-1},\ UNE_{t-1},\ CFSI_t,\ CBCC_t)$$

- Main case (of interest): DFM, GBR[3] (**23** predictors)

$$\widehat{GDP}_{t+1} = \ \mathcal{F}(GDP_{t-2},\ CPI_{t-1},\ UNE_{t-1},\ CFSI_t,\ CBCC_t,\ Payments_t).$$

[2] CPI: Consumer Price Index, UNE: Unemployment, CFSI: Canadian Financial Stress Indicator, CBCC: Consumer Board's Confidence Index

[3] OLS: Ordinary Least Squares, DFM: Dynamic Factor, GBR: Gradient Boosting

Key Results

RMSE on out-of-sample testing period[a] at $t+1$ prediction horizon:

Target	Benchmark[b]	Main-DFM[c]	Main-ML[d]	% RMSE Reduction[e]
GDP	3.97	2.98	2.43	39*
RTS	8.47	6.36	5.44	36*
WTS	7.17	6.18	4.28	41*

[a] Training: Mar 2005 to Dec 2018 and testing: Jan 2019 to Dec 2020

[b] Benchmark: OLS using first available lagged target and other base case variables

[c] Main-DFM: Payments data along with the benchmark variables in the DFM model

[d] Main-ML: Payments data along with the benchmark variables in the gradient boosting model

[e] % Reduction in RMSE using ML model with payments data over the benchmark model

* Denote statistical significance at the 10% over benchmark

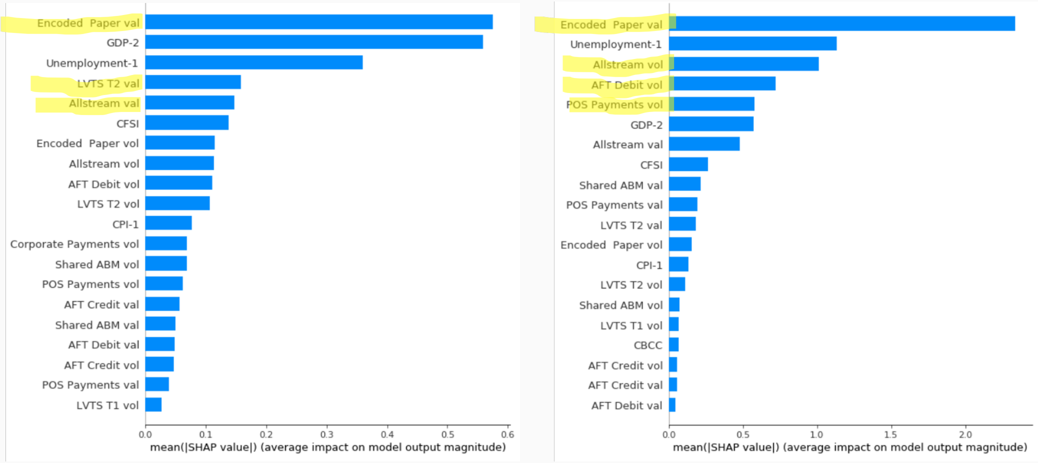
Model Interpretation and Payments Data Contribution

Local Interpretation

Real-time insights into marginal contributions of individual payments streams

Global Interpretation

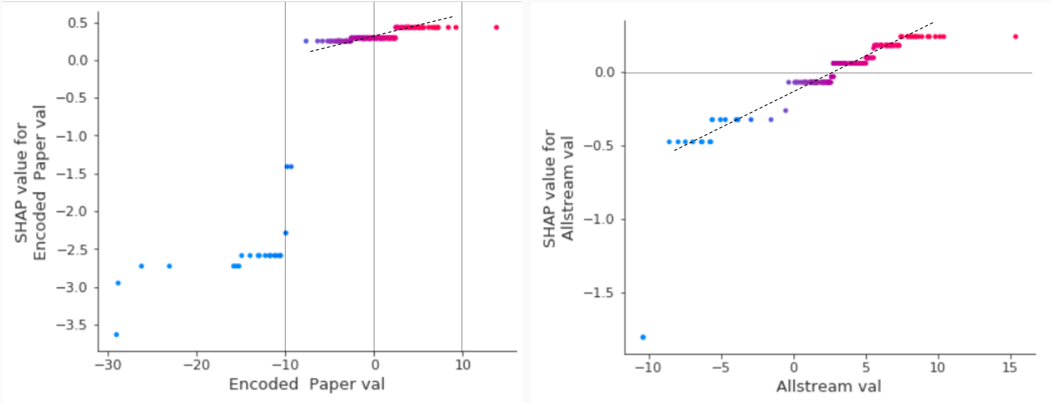
Retail payments streams rank high and their importance increases during crisis periods



Left: full sample and Right: Covid-19 period (Mar to Dec 20)

Dependence plots

Contribution of some of the payments streams is asymmetrical and nonlinear



Conclusions

This paper substantiates the use of payments data and ML models for macroeconomic prediction and provides a set of tools to overcome associated challenges:

- Payments data provide economic information in **real-time**
- Usefulness of payments data increases during **crisis** periods
- Machine learning can help improve prediction **accuracy**
- **Tailored** cross-validation approach is helpful for ML model tuning
- Interoperability tools can improve **effectiveness** of these models for policy use

Thank you!