Macroeconomic Predictions using Payments Data and Machine Learning*

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

Objective

Demonstrate the usefulness of payments data and machine learning (ML):

- Use payments data from Canada's retail and large value payments systems
- Use the following ML models: elastic net, artificial neural network, random forest, and gradient boosting
- Estimate current period (nowcast) GDP, retail, and wholesale trade sales

Address the associated challenges: interpretability and overfitting

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

Motivation

Macroeconomic Nowcasting:

- Delay: official estimates are released with a substantial lag
- Uncertainty: undergo multiple revisions sometime after years
- Unprecedented economic impacts of the crisis
- Unreliability of traditional models due to their reliability on the lagged data

Payments Data & Machine Learning:

- Payments data is gathered electronically hence, available promptly
- Payments data is error-free: Has no measurement or sampling error
- Payments data captures a broad range of the economic activities
- ML models can efficiently handle wide data and manage collinearity and they can help capture nonlinear interactions

Results Preview

Payments system data and ML models can lower nowcast errors significantly[1]:

- 35 to 40% reduction in RMSE for predicting GDP, retail and wholesale sales over a benchmark[2] and 15 to 25% reduction over payments data with factor model
- Out-of-sample model performance is relatively higher during the COVID-19 crisis period than the pre-COVID "normal" period
- Model interpretation reveals that, a few payments streams are important over entire nowcasting periods and their importance increases during crisis periods[3]
- Proposed cross-validation strategy help to reduce nowcasting RMSEs (6-12%)

[1] Gradient boosting model performed consistently better than other models
[2] Our benchmark is mixture of lagged and timely indicators in a linear model
[3] Adjusted paper stream, sum of all ACSS streams, AFT and POS debits streams contribute more

Literature

Payments Data for macroeconomic prediction:

- Galbraith & Tkacz (2018): Nowcasting with payments system data
- Aprigliano et al. (2019): payment system data to forecast the economic activity
- Chapman and Desai (2021): Nowcasting with retail payments data during crisis

Machine Learning for macroeconomic prediction:

- Richardson et al. (2020): Nowcasting GDP using machine learning
- Maehashi and Shintani (2020): GDP prediction using factor models and ML
- Coulombe et al. (2021): Can machine learning catch the Covid-19 recession?

Outline

1. Data
2. Methodology
3. Interpretability
4. Overfitting
5. Results

Data

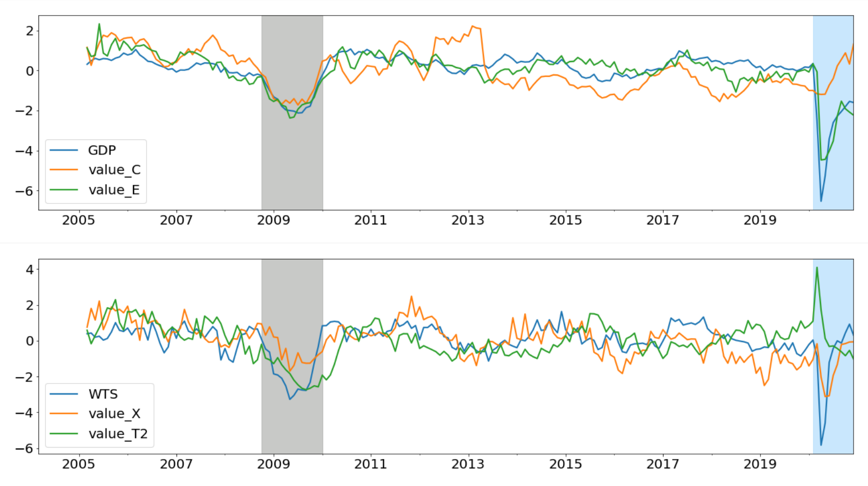
Canadian ACSS and LVTS Data

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

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

First six streams are representative of twenty payments instruments processed separately in the ACSS

Payments Data for Prediction



Standardization year-over-year growth rate comparisons of targets and payments streams.

C-AFT Credit, E-Encoded Paper, X: Corporate Payments, T2: LVTS-T2 and WTS: Wholesale Trades

Payments Data: Opportunities & Challenges

Opportunities:

- Timely: available immediately after the end of the period
- Precise: carry no sampling and measurement error
- Comprehensive: capture a broad range of financial activities across the country

Challenges:

- Many changes in the ACSS streams (mainly due to technological advancements)
- Not all retail payment schemes are in our data set (no credit card payments)
- On-us transactions are not captured (if payer and payee have same banks)
- Underlying data are non-stationary (who uses cheques anymore?)
- Payments data have a strong seasonal component (need seasonal adjustments)

Methodology

Models

List of model employed:

- **Ordinary least squares (OLS):** Minimizing the sum of the squares of the differences
- **Dynamic Factor Model (DFM):** Captures dynamics of large set of predictors into small number of latent factors
- **Elastic Net Regularization (ENT):** Minimizing the sum of the squares of the differences with penalty factors
- **Artificial Neural Network (ANN):** Multiple layers of artificial neurons sandwiched between input and output layers
- **Random Forest Regression (RFR):** Forest of many independent regression trees each built from subset of the training set
- **Gradient Boosting Regression (GBR):** Sequence of small trees are built on a repeatedly modified training dataset

Machine Learning Models: Opportunities & Challenges

Opportunities:

- Handle non-traditional and large-scale datasets and manage collinearity
- Capture sudden, large, and nonlinear relationships
- Emphasis on improving prediction accuracy

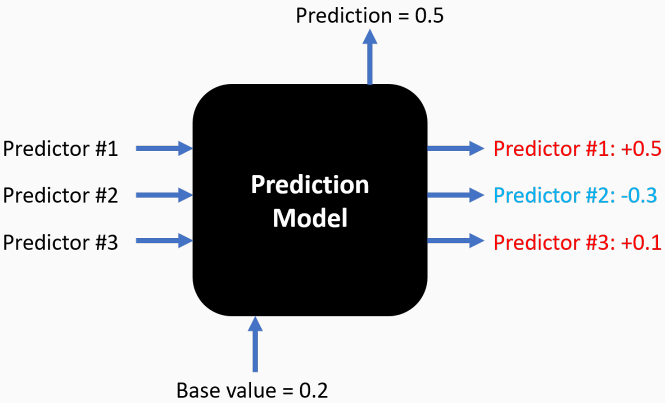
Challenges:

- Interpretability
- Overfitting
- Large-scale data

Interpretability

Shapley Values: SHAP[4]

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)



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

SHAP: Advantages & Disadvantages

Advantages:

- Theoretical foundation
- Model independent
- Local and global interpretation

Disadvantages:

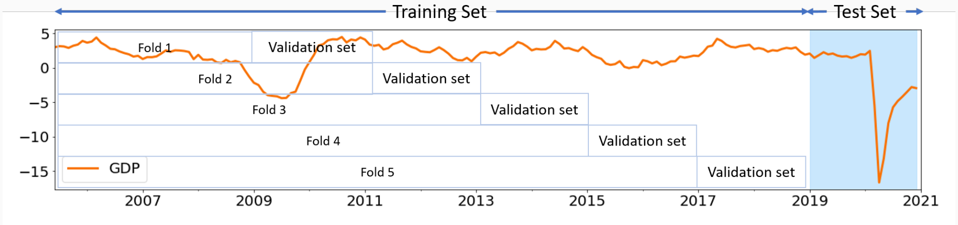
- Computationally expensive with increasing number of predictors
- Parametric models suffer from collinearity in the predictors
- It is possible to create intentionally misleading interpretations[5]

[5] Slack, Dylan, et al. (2019): Fooling LIME and SHAP: Adversarial attacks on post hoc explanation methods

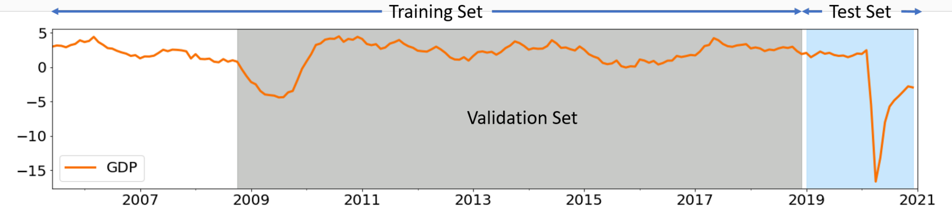
Overfitting

K-fold Cross-validation: Randomized expanding window

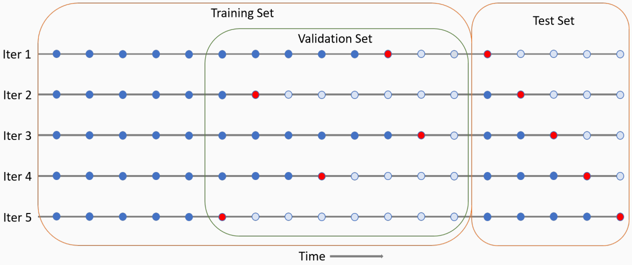
Standard approach for time-series:



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

Results

Nowcasting Models: Case specifications

The nowcasting horizon ($t+1$) is based on the payments data availability t

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)[6]

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

- Main case (of interest): DFM, ENT, RFR, GBR, ANN[7] (**23** predictors)

$$\widehat{GDP}_{t+1} = \mathcal{F}(GDP_{t-2},\ CPI_{t-1},\ UNE_{t-1},\ CFSI_{t},\ CBCC_{t},\ Payments_{t}).$$

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

[7] OLS: Ordinary Least Squares, DFM: Dynamic Factor, ENT: Elastic Net, RFR: Random Forest, GBR: Gradient Boosting, ANN: Neural Network

Nowcasting Models: Results

RMSE on out-of-sample testing period[a]

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	5.32	37*
WTS	7.18	5.93	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

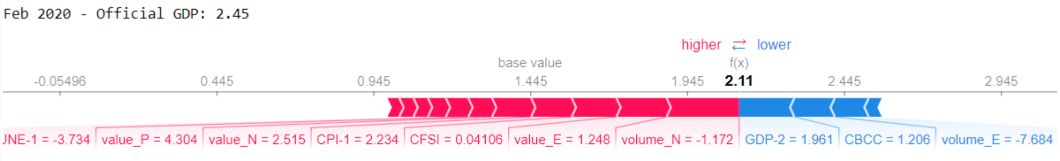
[d] Main-ML: Payments data along with the benchmark variables in the ML model (only the best among ENT, RFR, GBR, ANN is showed)

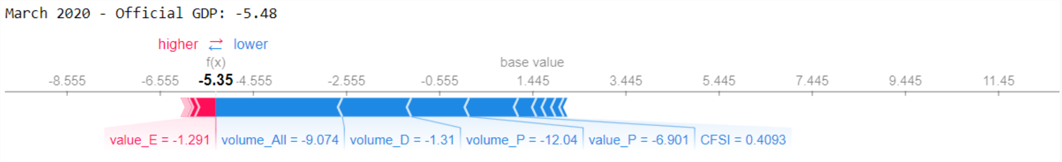
[e] % reduction in RMSE using ML model with payments data over the benchmark model

* denote statistical significance at the 10% over benchmark

ML Models: Interpretation

Local interpretation: GDP nowcast using gradient boosting (train: Mar 05 to Dec 20)

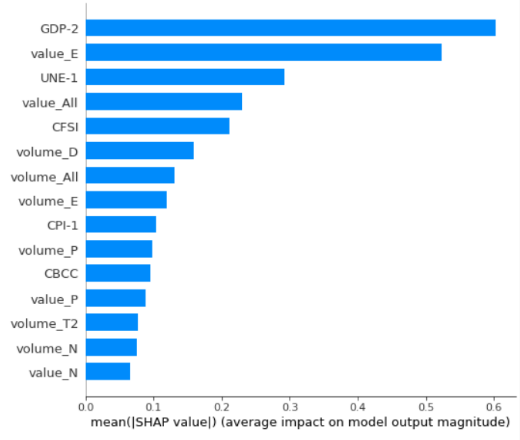


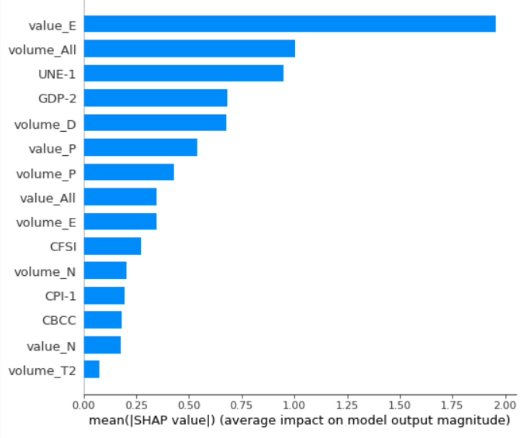


Force plots for Feb and Mar 2020. Red are positive Shapley values and blue are negative Shapley values. $f(x)$ is the model prediction and the base value is average of all predictions

ML Models: Interpretation

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





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 and help reduce dependence on lagged variables (during normal times and crisis periods)
- Machine learning provide set of econometric tools to effective process various payments streams and capture sudden and large effects of crisis
- Shapley value-based SHAP approach is useful to get insights into the ML model predictions (local and global interpretations)
- Proposed cross-validation technique can help reduce overfitting and improve prediction accuracy in macroeconomic nowcasting models

Thank you!