

Using Payments Data to Nowcast Macroeconomic Variables During the Onset of Covid-19*

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

Introduction

Predict the current state of the economy (nowcasting) using timely data:

- We use Canadian retail payments system data
- Nowcast macroeconomic indicators during crisis: GFC-08 and COVID-19 shock
- Test the usefulness of machine learning models for nowcasting during crisis

Simple exercise: E.g., use July's data to provide estimate of July's GDP on Aug 1st

Macroeconomic Nowcasting:

- Delay: Official estimates are released with a substantial lag
- Uncertainty: Undergo multiple revisions sometime after years

Macroeconomic Nowcasting During Crisis:

- Unprecedented speed of policy changes
- Unconventional economic impacts as we delve into the unfamiliar world
- Unreliability and slow response of traditional data and models used for predictions

Retail Payments System Data:¹

- Timely: Gathered electronically hence, available promptly
- Error-free: Has no measurement or sampling error
- Variety: Captures a broad range of the economic activities

Machine Learning Models:^{2,3}

- Efficiently handle wide data and manage collinearity
- Methodically capture non-linear interactions
- Emphasis on improving prediction accuracy

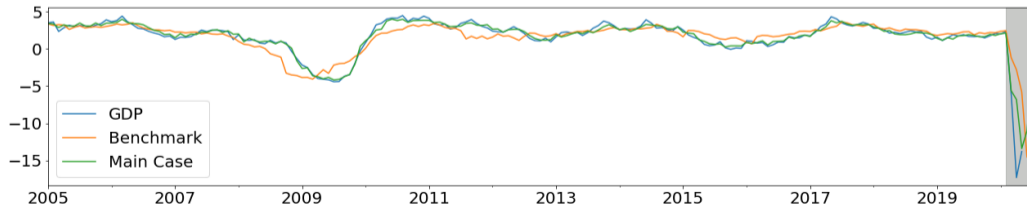
¹ Automated Clearing and Settlement System (ACSS)

² Elastic Net (ENT), Support Vector Regression (SVR), Random Forest (RF), Gradient Boosting (GB)

³ Galbraith & Tkacz(2017), Aprigliano et al.(2017), León et al.(2018), Richardson et al.(2018), Kapetanios & Papailias(2018), Bounie et al.(2020)

Substantial improvements in macroeconomic nowcasting accuracy during crisis:

- Global financial crisis: Overall 15% to 45% reduction in RMSE for predicting different macroeconomic indicators over a benchmark
- COVID-19 shock: Model provides early estimates of massive impacts of shock
 - Predicted YoY GDP growth rates for Jun and Jul 2020 are -10.8% and -2.97%
 - Prediction falls short for official estimates which are released with a short delay



Data

Automated Clearing and Settlement System (ACSS)

- ACSS settles the majority of retail and small-value payment items
- In 2019, ACSS handled an average of 33 million payments items per day, with an average daily total value of 29 billion dollars
- Twenty-four types of payments instruments (streams)
- Streams can be categorized into two groups: Electronic streams, Paper streams
- Streams aggregated at daily level are available starting 1999 (~ 20 years of data)

Effects of Covid-19 Shock: Monthly stream

Figure 1: Compared to the same period in 2019, value dropped by 32% and volume by 41%

Effects of Covid-19 Shock: Monthly stream

Figure 2: Compared to the same period in 2019, value dropped by 33% and volume by 39%

Some Issues with Our Dataset

- 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 ACSS data is non-stationary (who uses cheques anymore?)
- Payments migration due to non-economic reasons (due to technological changes)
- Nature of current Covid-19 crisis is different than global financial crisis

Methodology & Results

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

To nowcast July's GDP growth rates on August 1st, i.e., at $t + 1$, we use **payments data** and **Canadian Financial Stress Indicator (CFSI)** for July (at t), and GDP growth rate of May (at $t - 2$):

- Base case (benchmark): OLS (2 predictor)⁴

$$\hat{y}_{t+1} = f(y_{t-1} \text{ or } t-2 \text{ and } c_t) \quad (1)$$

- Main case (of interest): OLS, ENT, SVR, RF, GB⁵ (**26** predictors)⁶

$$\hat{y}_{t+1} = f(y_{t-1} \text{ or } t-2, c_t \text{ and } p_t) \quad (2)$$

⁴ First available lagged-target (y_t) and CFSI (c_t) - Composite measure of systemic financial market stress for Canada (Duprey (2020))

⁵ OLS: Ordinary Least Squares, ENT: Elastic Net, SVR: Support Vector Regression, RF: Random Forest, GB: Gradient Boosting

⁶ 24 Payments streams (p_t , 12-values, 12-volumes): This includes 11 streams (some of which are adjusted) and Allstream (sum of all streams)

Results for two crisis periods

Case specifications:

- Global financial crisis: To test the usefulness of ACSS payments data
- COVID-19 shock: Use payments data to provide early estimates of the shock

Data specifications:

- Payments data used range from Jan 2005 to Jul 2020 ($p = 187$ sample points)
- As features we use 24 payments streams (value and volume for 12 instruments)
- As targets we use following macro indicators: GDP, RTS, WTS, HPI, CPI, UNE⁷

⁷ RTS-Retail Trade Sales, WTS-Wholesale Trade Sales, CPI-Consumer Price Index, HPI-New House Price Index and UNE-Unemployment

RMSE on out-of-sample testing period^a

Target	Benchmark ^b	Main-OLS ^c	Main-ML ^d	% Reduction (RMSE)
GDP	1.18	0.80	0.77 ^{**}	35
RTS	4.12	3.12	2.65 ^{**}	36
WTS	4.73	3.21	2.72 ^{***}	43
CPI	0.54	0.42	0.38 [*]	30
HPI	0.39	0.34	0.33	16
UNE	6.21	5.93	5.48	12

^a Training: Jan 2005 to Oct 2008 ($p = 46$) and testing: Nov 2008 to Jan 2010 ($p = 14$)

^b Benchmark: OLS using first available lagged target and CFSI

^c Main-OLS: Payments data along with the benchmark variables in the OLS model

^d Main-ML: Payments data along with the benchmark variables (best among ENT, SVR, RF, GB)

^{*}, ^{**}, ^{***} denote statistical significance at the 10, 5, and 1%

Out-of-sample nowcasting for July 2020^a

	Jul 2020 Predictions (on Aug 1 st)		
	Actual	Benchmark ^b	Main case ^c
GDP	-3.99	-6.47	-2.97
RTS	2.90	-5.96	1.58
WTS	1.41	-9.60	-0.71
CPI	0.42	0.77	1.37
HPI	1.70	1.15	1.46
UNE	89.2	7.98	62.6

a Training period: Jan 2005 to Mar 2020 ($p = 183$) and testing period: Apr and July 2020.

b Benchmark: OLS using the first available lagged macro variable and financial market data

c Main case: payments data along with the base case variables

Conclusions

- The payments data carry useful information about extreme financial events, and it can help improving macroeconomic nowcasting during crisis
- Macrovariable are complex and payments streams in isolation are not sufficient, but they could add value if used with other predictors for official nowcasting
- Allstream and Encoded Paper values streams are the most important predictors
- Global financial crisis: Overall, 15% to 45% reduction in RMSE over benchmark
- ML-based models can further improve the prediction accuracy (5 to 15%)

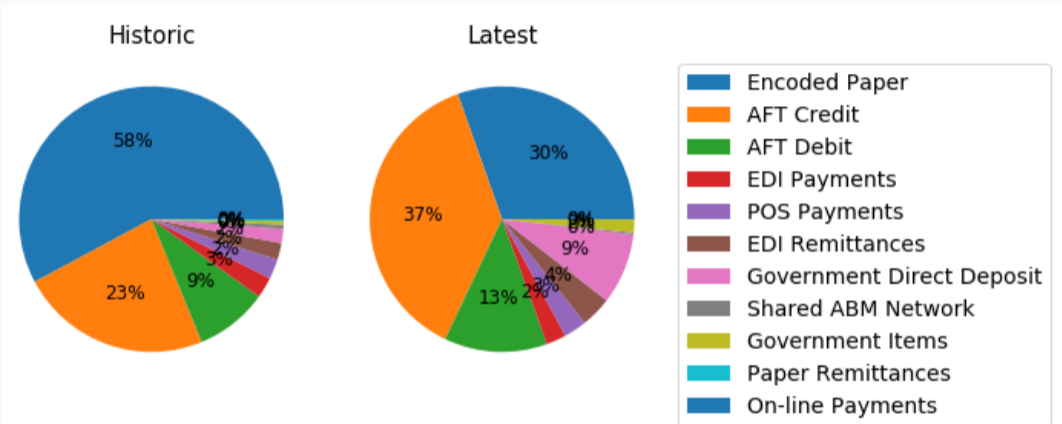
Thank you!

ACSS Payments Streams: Used in this study

ID	Label	Short description
C	AFT Credit	Direct deposit (DD): payroll, account transfers
D	AFT Debit	Pre-authorized debits (PADs): bills, mortgages, utility
J	On-line Payments	Electronic payments using a debit card through internet
M	Government DD	Reoccurring social payments: social security, tax refunds
N	ABM Network	Debit card payments to withdraw cash
P	POS Payments	Point of sale payments using debit card
X	EDI Payments	Exchange of corporate-to-corporate payments
Y	EDI Remittances	Corporate electronic bill payments
E	Encoded Paper	Paper bills of exchange: cheques, bank drafts, paper-PADs
F	Paper Remittances	Corporate bill payments. It is identical to stream Y
G	Government Items	Paper items: Government of Canada paper
All	Allstreams	Sum of all streams in the ACSS

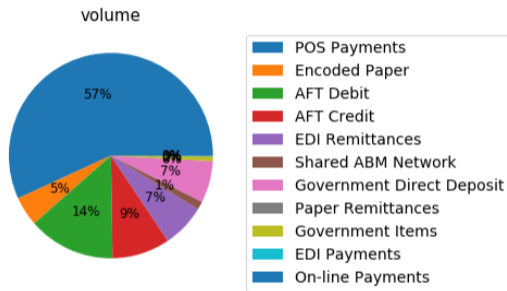
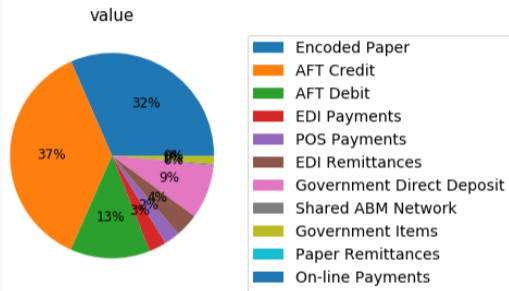
We make adjustments in E, J, P, and G (these 11 series represent 20 streams)

ACSS Payments Streams: Value shares



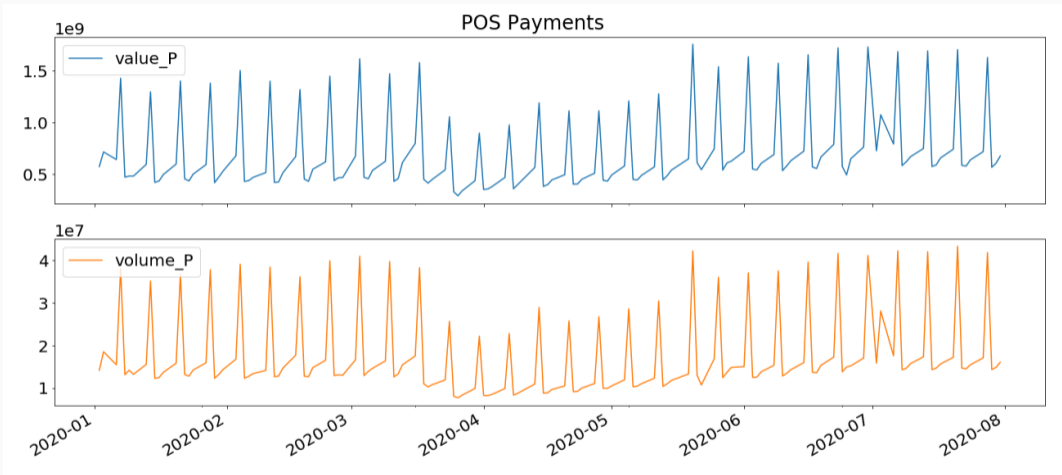
Value shares (dollar amount) of payments streams after making adjustments for period:
Historic-**Jan 1999 to Jul 2020** and Latest-**Apr 2020 to Jul 2020**

ACSS Payments Streams: Shares during Covid-19 period



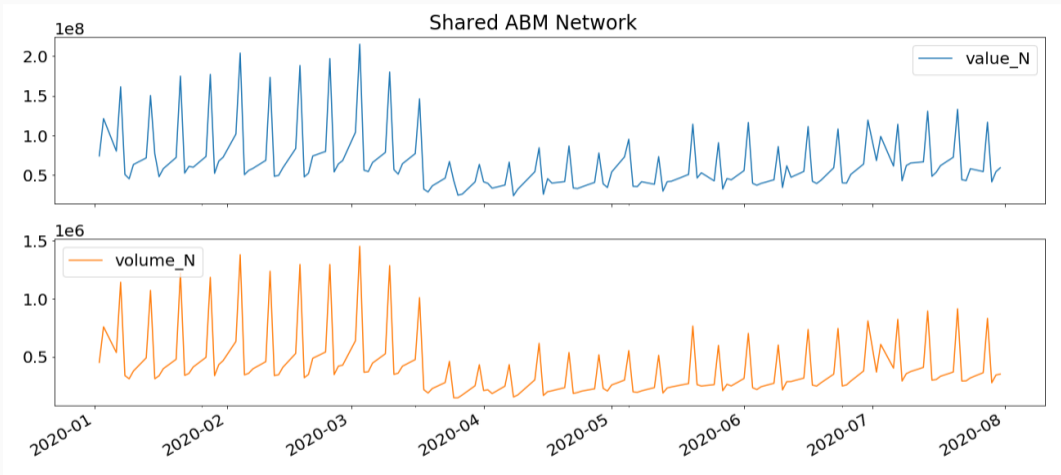
Shares of payments streams in terms of value and volume after making adjustments for period:
Mar 2020 to May 2020

Effects of Covid-19 Shock: Daily stream



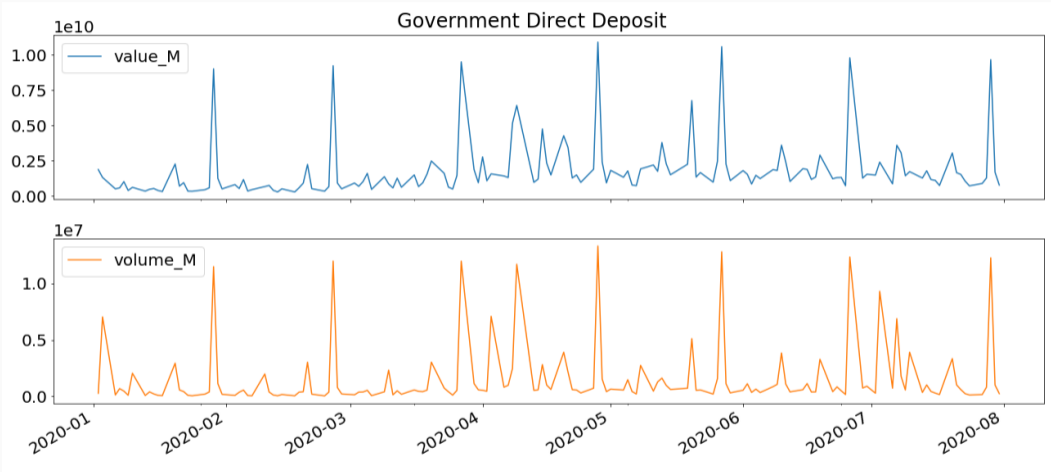
Large drop starting late March and recovered to the pre-COVID-19 level starting late May

Effects of Covid-19 Shock: Daily stream



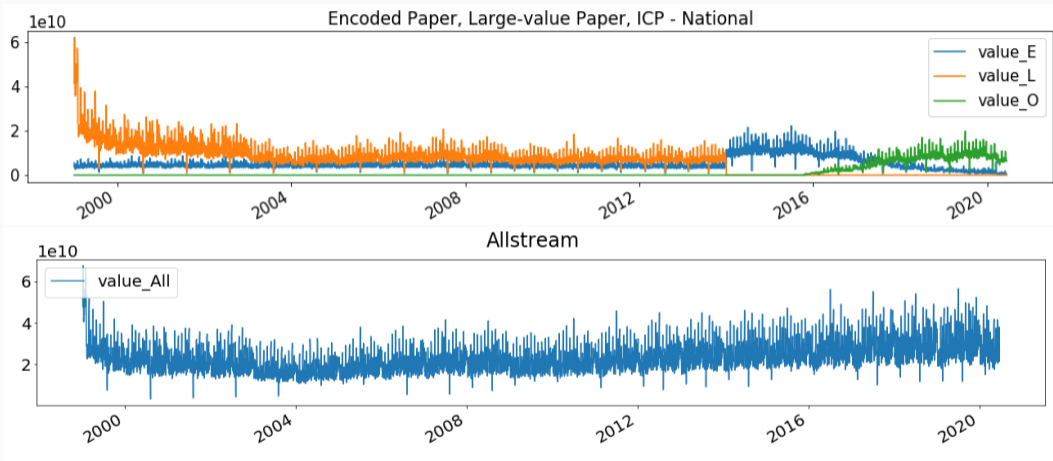
Large drop starting late March and small recovery starting late May

Effects of Covid-19 Shock: Daily stream



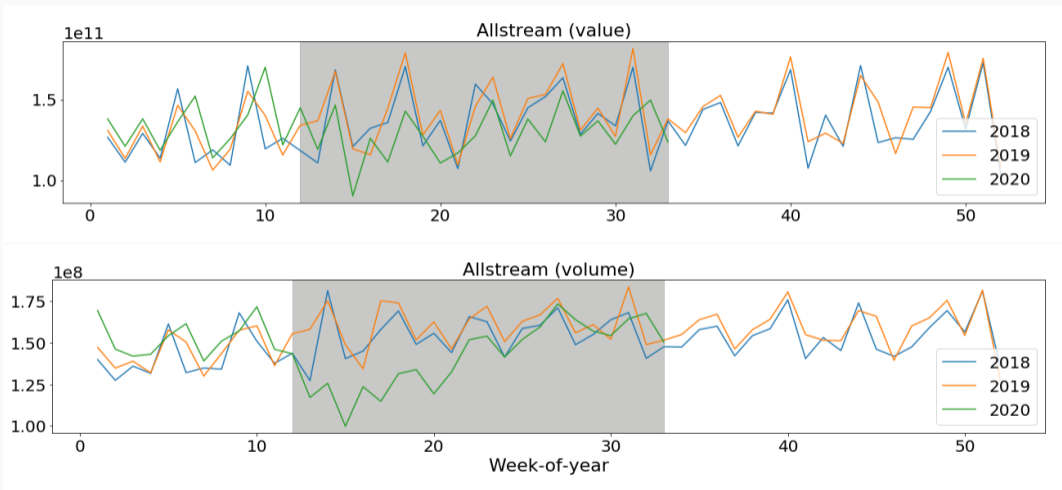
Significant increase value and volume settled in this stream starting early April

ACSS Payments Streams: Adjustments

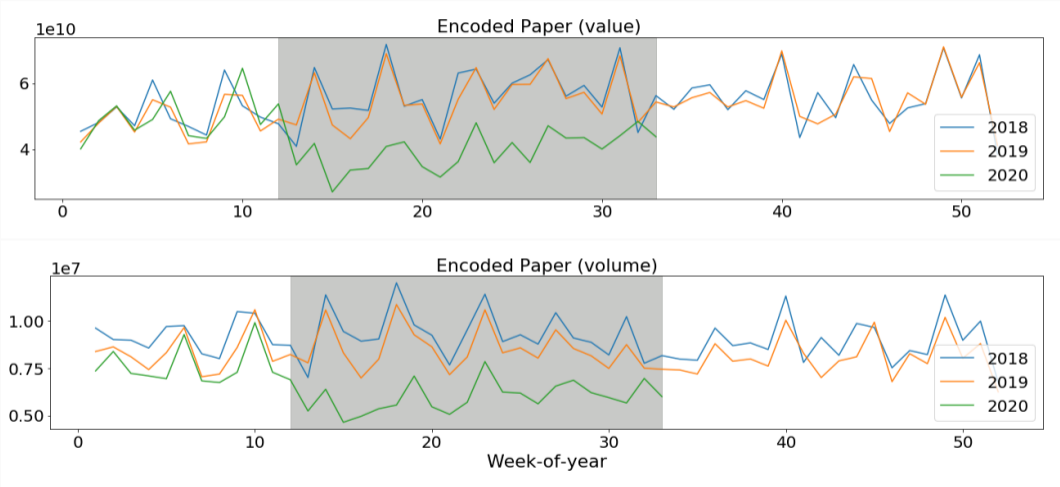


Multiple changes over time in different streams, mainly due to technological advancements

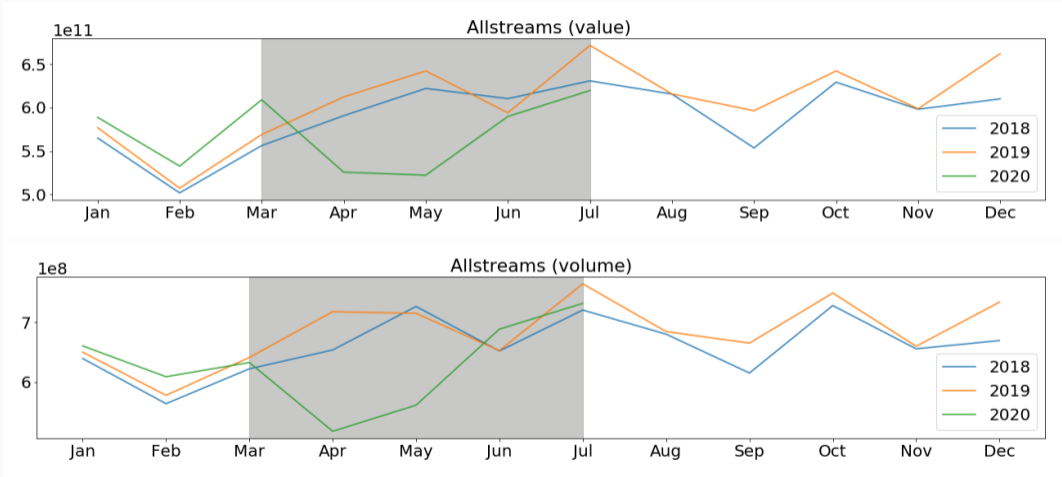
Effects of Covid-19 Shock: Weekly stream



Effects of Covid-19 Shock: Weekly stream



Effects of Covid-19 Shock: Monthly stream



Effects of Covid-19 Shock: Monthly stream

Effects of Covid-19 Shock: Monthly stream

Targets Vs Selected ACSS Streams: Pairwise correlations during crisis

Most of the ACSS streams have a strong correlation with macroeconomic indicators during the global financial crisis period

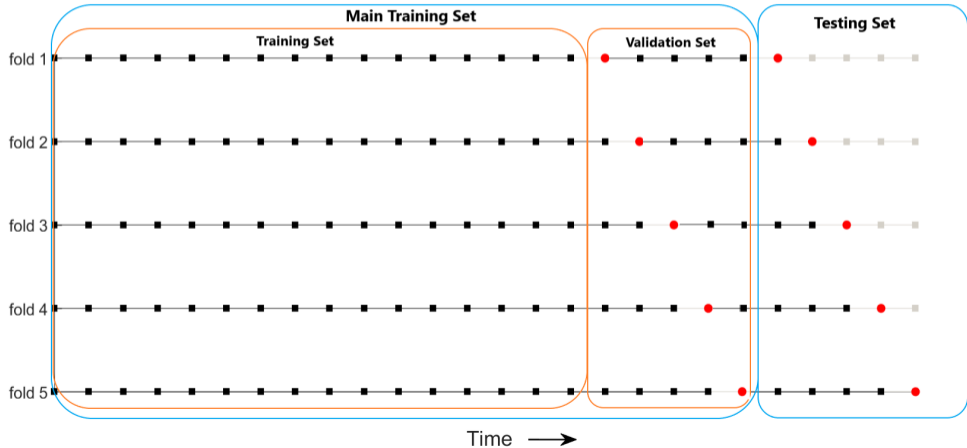
	All-value	E-value	C-value	Y-value	P-value	X-volume	D-value
GDP	0.94	0.93	0.82	0.81	0.80	0.80	0.75
RTS	0.84	0.80	0.78	0.40	0.83	0.75	0.72
WTS	0.94	0.93	0.82	0.77	0.74	0.80	0.78
HPI	0.83	0.85	0.68	0.87	0.64	0.61	0.56
CPI	0.76	0.78	0.67	0.83	0.76	0.65	0.58
UNE	-0.87	-0.88	-0.72	-0.86	-0.67	-0.66	-0.63

* Correlations are calculated for the period Oct 2008 to Jan 2010

* All-Allstream, E -Encoded Paper, C - AFT Credit, Y - EDI Remittances, P - POS Payments, X - EDI Payments and, D - Aft Debit

Model training using expanding window approach

- Model tuning and cross-validation using **nested validation set**



Model selection in main case for each macroeconomic variables:

1. Compute prediction scores for payments streams using univariate regression tests
2. Incorporate one stream at a time (based on scores) for prediction
3. Repeat steps 1 and 2 for each model and get in-sample and out-of-sample RMSEs
4. Select the model with least in-sample and out-of-sample RMSEs

- Galbraith & Tkacz (2017): Nowcasting with payments system data
- Aprigliano et al. (2017): Payment system data to forecast Italian GDP
- León et al. (2018): Nowcasting economic activity with electronic payments data
- Richardson et al. (2018): Nowcasting New Zealand's GDP using machine learning
- Kapetanios & Papailias (2018): Big data & macroeconomic nowcasting review
- Bounie et al.(2020):Consumers response to Covid-19 using french transaction
- Chapman and Desai (2020): Nowcasting with payments data and ML