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A Large Canadian Database for Macroeconomic Analysis[*]

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Résumé/Abstract

This paper provides a large-scale Canadian macroeconomic database and shows its usefulness for empirical macroeconomic analysis. The dataset contains hundreds of Canadian and provincial economic indicators. It is designed to be updated regularly and real-time vintages are publicly available. It relieves users to deal with data changes and methodological revisions. We show four useful features of this dataset for macroeconomic research. First, the factor structure explains a sizeable part of the variation of the dataset and appears as an appropriate means of dimension reduction. Second, the dataset is useful to capture turning points of the Canadian business cycle. Third, it has substantial predictive power when forecasting key macroeconomic indicators. Fourth, the richness of the panel is used to study the effectiveness of monetary policy across regions and sectors.

Mots clés/Keywords: Big Data; Factor Model; Forecasting; Structural Analysis

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1 Introduction

Large datasets are now very popular in empirical macroeconomic research. Stock and Watson (2002a,b) have initiated the breakthrough by providing the econometric theory and showing the benefits in terms of macroeconomic forecasting, while Bernanke et al. (2005) have inspired the literature on impulse response analysis in the so-called data-rich environment. Since then, many theoretical and empirical improvements have been made, see Stock and Watson (2016) for a recent overview. Most of this literature is built on US datasets. Therefore, McCracken and Ng (2016, 2020) proposed standardized version of a large monthly and quarterly US datasets that are regularly updated and publicly available at the FRED (Federal Reserve Economic Data) website. No such developments have been made with Canadian macroeconomic data, so the objective of this work is to fill the gap and provide a user-friendly version of a large Canadian dataset suitable for many types of macroeconomic research. Since Canada is an example of a small open economy, this dataset will also be of interest for a wide range of applications in international economics.

In this paper, we construct a large-scale Canadian macroeconomic database in monthly frequency and show how it can be useful for empirical macroeconomic analysis with several illustrative examples. The dataset contains hundreds of Canadian and provincial raw economic indicators observed from 1914. It is designed to be updated regularly in real time through StatCan database and is publicly available.[1] It relieves users to deal with data changes and methodological revisions. We provide a balanced and stationary panel starting from 1981 that is suitable for work in business cycle fluctuations. The quarterly panel is available as well, and is essentially constructed by averaging the monthly series and adding the GDP and its components that are only observable at quarterly frequency. In this paper we only study the monthly panel.

Early attempts to construct large Canadian macroeconomic datasets are Gosselin and Tkacz (2001) and Galbraith and Tkacz (2007). Boivin et al. (2010) updated and merged data from those previous studies yielding a panel that covered the period 1969 - 2008 and had 348 monthly and 87 quarterly series. Then, Bedock and Stevanovic (2017) constructed a new dataset of 124 monthly variables observed from 1981 to 2012. Their selection of series was based on the Canadian counterparts of US data used in Bernanke et al. (2005). More recently, Sties (2017) has built a much smaller monthly dataset containing mostly financial series and few real activity indicators. Stephen Gordon has also been updating some relevant Canadian indicators[2], while the Bank of Canada released its Staff Economic Projections database, as documented in Champagne et al. (2018, 2019).[3] Our data selection is inspired by McCracken and Ng (2016) when it comes to major groups of economic variables. Given that Canada is a small open economy, the dataset contains many international trade, financial flows and natural resource indicators.

[1]Data can be accessed here: http://www.stevanovic.uqam.ca/DS_LCMD.html.
[2]See Project Link at https://www.ecn.ulaval.ca/s̃gor.
[3]Data are available here: https://www.bankofcanada.ca/rates/staff-economic-projections/.

We illustrate several useful features of this dataset for macroeconomic research. **First**, we show that our panel is likely to present a factor structure and that common factors explain a sizable portion of variation in Canadian and provincial aggregate series. The principal component analysis of the dataset identifies few driving forces of the Canadian economy such as GDP in business and financial sectors, term structure, exchange rates, unemployment duration, international transaction net flows and oil production. **Second**, the dataset is useful to capture turning points of the Canadian business cycle. Using Probit, Lasso and factor models we show that this dataset has substantial explanatory power in addition to the standard term spread predictor. **Third**, the dataset provides information to substantially improve the predictive accuracy when forecasting key real macroeconomic indicators. Factor and sparse models, random forests and regularized complete subset regressions show good performance in forecasting real activity variables such as industrial production, employment and unemployment rate, as well as CPI and Core CPI inflation. In the case of credit market aggregates, only the regularized complete subset regressions and random forests are resilient, while practically no model improve the predictive accuracy for housing starts and building permits. **Fourth**, the dataset can serve for structural impulse response analysis. We document heterogenous effects of monetary policy on different sectors of the Canadian economy and across regions. The passage to inflation targeting since 1992 coincides with a decrease in those differences, but some regional heterogeneity still pertains and may pose a challenge for the Bank of Canada in its role to further stabilize the economy.

The rest of the paper is organized as follows. Section 2 describes the construction of datasets and performs the factor analysis. Section 3 shows the informational content of this dataset in detecting recession dates. In Section 4 we conduct a pseudo-out-of-sample forecasting exercise to test the capability of the dataset to help predicting main Canadian macroeconomic variables. Section 5 performs an impulse response analysis and Section 6 concludes.

2 Datasets

In this section, we start by describing the construction of the dataset and, in particular, how we deal with several issues related to availability and statistical properties of the data. We then explore the factor structure of this dataset.

2.1 Construction of datasets

The Canadian monthly database comprises eight different groups of variables: production, labor, housing, manufacturers' inventories and orders, money and credit, international trade and financial flows, prices and stock markets. Whenever available, we included regional data covering the Atlantic provinces, Québec, Ontario, the Prairies and British Columbia, as well as provincial data. The complete list of series is available in the data appendix B. We decided to include a large number of housing market series since the housing cycle is an important feature of the business cycle (Leamer, 2015). In addition, given that Canada is a small open economy, we added more international trade, financial flows and natural resource indicators than one usually finds in the US applications.

In building this database, several problems are encountered. Some tables have unfortunately been discontinued and the new tables seldom go sufficiently far back in time to afford us a sizeable time frame. Therefore, we combine old and new time series to cope with this problem. This happens with data on production, housing, orders and import and export. For instance, GDP data for the period starting in January 1981 and ending today is split across two tables: 379-0027, going from 1981/01 to 2012/01 and 379-0031, starting only on 1997/01. There exist several procedures to combine two time series that share an overlapping period. de la Escosura (2016) reviews three splicing procedures and introduces a new one of his own. As he notes, this aspect of data analysis generally receives little attention with researchers often going for what he calls retropolation whereby the new time series is re-projected using the growth rates of the old time series. If the oldest observation of the new series is made at time T, the retropolated series over the previous time interval is given by:

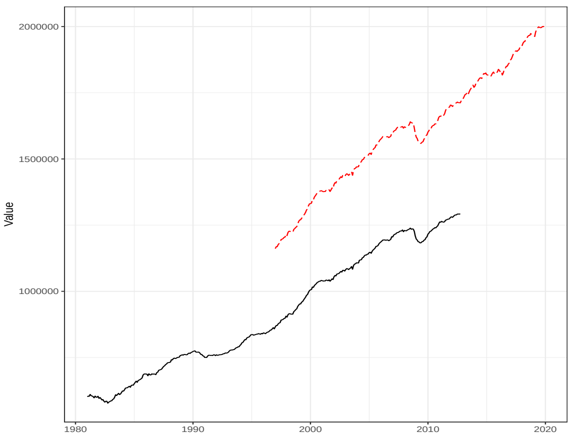
$$y_t := \left(\frac{y_T^{new}}{y_T^{old}} \right) y_t^{old}. \tag{1}$$

This corresponds to assigning all the measurement adjustment to the level of the old time series. However, by construction, all increasing time series will be retrospectively skewed upward. As de la Escosura (2016) notes, this is an undesirable feature if we are studying long-term growth, although it is mostly accurate over long time periods and in economies undergoing deep structural change, such as developing economies. Linear and non-linear interpolation schemes would, on the other hand, force the levels of the new series at T and of the old series at some other reference date, to be preserved, which means assigning all the modification to the observed growth rates of the old time series in between both references dates.[4] The choice of a splicing method therefore depends on the application and the beliefs of the researchers concerning what is best measured. In the construction of this database, we privilege the retropolation approach because we prefer to leave observed growth rates intact. For some series, this involves making hardly any changes as we can see in Figure 1.

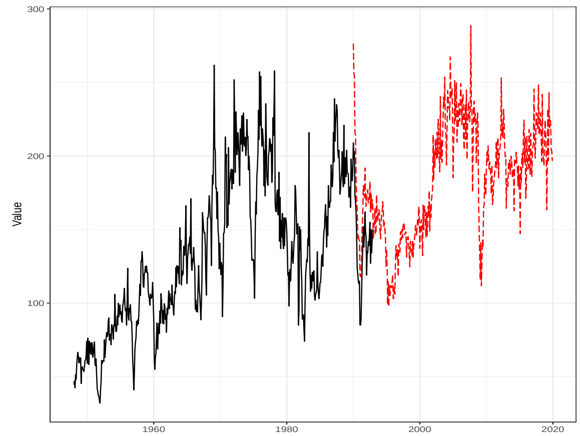
For imports and export series, there usually was a need to aggregate old series before splicing since old and new trade data do not share a common classification system. In the example provided below of exported consumption goods, we aggregate section 2 data on food, feed, beverages and tobacco, major group 4.23 on textile fabricated materials, and major group 5.11 on other consumption goods to approximate the consumer good class of the North American Prod-

[4] Interpolation schemes spare observed levels at specific dates, at the expense of modifying growth rates, the dates being strategically chosen because measurements are believed to be more accurate. de la Fuente Moreno (2014) also proposed a mixed splicing method that allows for a middle ground to be chosen by the researcher through a tuning parameter.

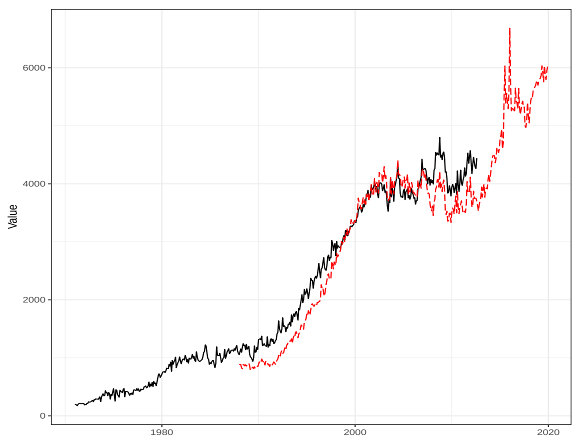
Figure 1: Examples of data splicing



(a) Gross domestic product (Canada)



(b) Housing starts (units, Canada)



(c) Exports of consumer goods (Canada)

Note: Old series are in black, while new (actual) series are in red.

uct Classification System (NAPCS). As is evident from the examples provided in Figure 1, viewing the old time series as noisy indexes of new time series seems justified by the high correlations in the overlapping periods.

Another problem concerns the seasonal behavior of a few important labor market time series, unemployment duration and initial claims, as they are not readily available in a seasonally adjusted format. To deal with this, we use the SEATS model based decomposition method that is provided along the X11 type capabilities of the ARIMA-X13-SEATS program of the US Census Bureau[5]. As a sanity check on the viability of the procedure, the Kruskal-Wallis test (Kruskal and

[5]This approach relies on a factorization of the AR lag polynomial of an ARIMA model whereby different roots of the polynomial can be assigned, respectively, to trend, transitory and seasonal components based on the fact each component will exhibit a different signature in the frequency domain. The ARIMA model is selected based on the automatic selection procedure provided by the program which relies on minimizing the BIC. For the implementation details, the reader is referred to the user manual of the US Census Bureau ARIMA-X13-SEATS program. Reader is referred to US Census Bureau (2017) X-13ARIMA-SEATS Reference Manual, available at

Wallis (1952)) for seasonal behavior is conducted both prior to and after the seasonal adjustment is performed. The result of the Kruskal-Wallis tests are shown in table 8 in Appendix A. The tests imply a rejection of the absence of seasonal behavior prior to the adjustments, but do not allow for rejection of the null hypothesis after the adjustments have been made as anticipated. Figures 11-12, in Appendix A.1, show the behavior of the model based adjustment procedure for few of unemployment duration and initial claims series.

Most of the series included in the database must be transformed to induce stationarity. We roughly follow McCracken and Ng (2016) and Bedock and Stevanovic (2017): most I(1) series are transformed in the first difference of logarithms, a first difference of levels is applied to unemployment rates and interest rates, first difference of logarithms is used for all price indexes, and housing data is featured in logarithms. Transformation codes are reported in data appendix.[6]

Our last concern is to balance the resulting panel since some series have missing observations. We opted to apply an expectation-maximization algorithm by assuming a factor model to fill in the blanks as in Stock and Watson (2002b) and McCracken and Ng (2016). We initialize the algorithm by replacing missing observations with their unconditional mean and then proceed to estimate a factor model by principal component. The fitted values of this model are used to replace missing observations. Examples of missing values include export and import series since the old tables went back only to 1988/01.

The resulting balanced and stationary panel is used in the rest of this paper.[7] We will consider only aggregate Canadian data in sections 3 and 4, while the richness of the provincial data will be explored in the section 5. The number of variables is likely to change over time as new data become available or some existing series end. In this paper, the Canadian data set contains 116 variables, while adding the provincial data gives a panel of 386 time series.

2.2 Number of Factors

Estimating the number of factors is an empirical challenge. Usually the first step is to plot the eigenvalues of the correlation matrix of data (scree plot) as well as the average explanatory power of consecutive principal components (trace). These are reported in Figure 2 for both panels: aggregate data only (CAN) and aggregate plus provincial data (CAN+Prov). The results are typical for macroeconomic panels. There is no clear cut separation among eigenvalues, and the explanatory power grows slowly with the number of factors. However, we remark that in the case of the Canadian panel 10 principal components explain almost 50% of variance of all variables, which is quite satisfactory. This suggests that the factor representation of Canadian macroeconomy is an

https://www.census.gov/ts/x13as/docX13AS.pdf

[6] Some of those transformations are questionable, e.g. keeping unemployment or interest rates in levels rather than applying first differences. We provide raw data as well so users can apply any transformation of their choice. This can potentially improve predictability as in Goulet Coulombe et al. (2020).

[7] This dataset ends on 2019M12 and have been constructed from March 2020 vintage. Changes can occur across vintages when some series become unavailable, such as the CERI_new: Canadian-Dollar Effective Exchange Rate Index.

Table 1: Estimating the number of factors in CAN_MD

	Canada	Canada + Provinces
BN02	6	5
ABC	6	6
ON	0	2
AH	2	1
HL	4	4
BN07	4	6
AW	4	4

Note: This table lists the number static and dynamic factors estimated by various statistical procedures.

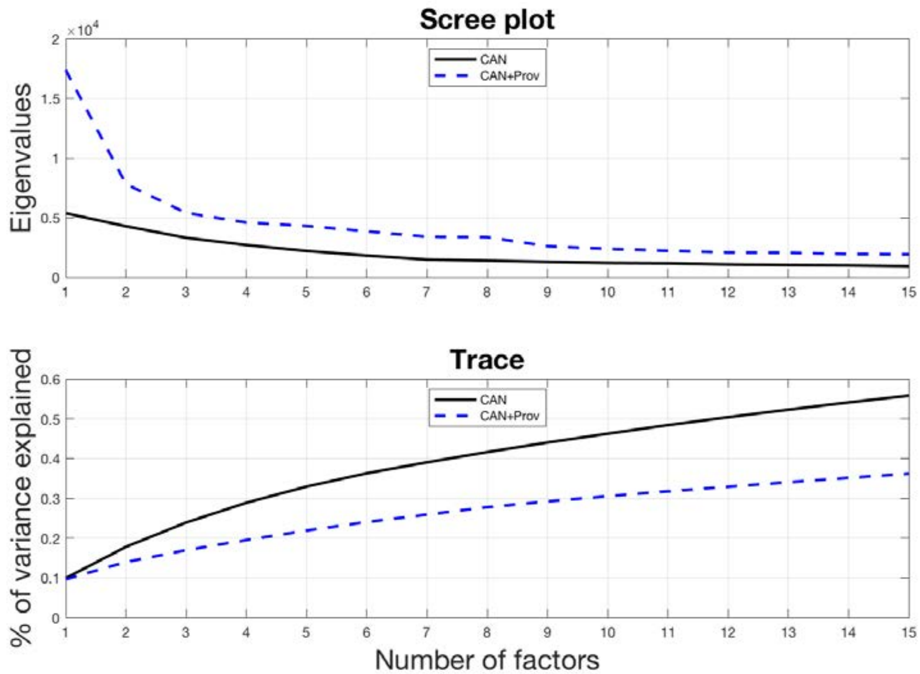
appropriate means of dimension reduction. Adding hundreds of regional time series reduces the explanatory power of the common factors which is not surprising. Considering groups of highly correlated variables tends to deteriorate the ability of principal components to recover the factor space (Boivin and Ng, 2006).

Many statistical decision procedures have been proposed to select the number of factors (see Mao Takongmo and Stevanovic (2015) for a review). Table 1 reports the number of factors estimated by the following methods: (BN02) Bai and Ng (2002) IC_{p2} information criterion; (ABC) modified version of (BN02) by Alessi et al. (2010); (ON) Onatski (2010) test based on the empirical distribution of eigenvalues; (AH) Ahn and Horenstein (2013) eigenvalue ratio test; (HL) Hallin and Liska (2007) test for the number of dynamic factors; (BN07) Bai and Ng (2007) test for the number of dynamic factors; and finally (AW) Amengual and Watson (2007) information criterion for the number of dynamic factors. (ON) and (AH) are known to be very conservative – and sensitive to the presence of weaker factor structures – and they indeed identify only few sources of common variation. (BN02) and (ABC) suggest 6 static factors for the aggregate panel and 5 to 6 in the case of the panel augmented by the regional series. The number of dynamic factors is estimated between 4 and 6 according to (HL), (BN07) and (AW).

It is also common in the literature to verify the stability of the factor structure in terms of the number of common components. Figure 3 plots the number of factors selected recursively by Bai and Ng (2002) and Hallin and Liska (2007) methods.[8] We observe that the number of static and dynamic factors is generally increasing since 1990, a similar pattern found with other large macroeconomic datasets (McCracken and Ng, 2016; Goulet Coulombe et al., 2021). Many explanations on the time-varying nature of the number of factors are plausible: structural changes in terms of the correlation structure, presence of group-specific factors, finite-sample sensitivity of selection procedures, and so on. We are not investigating those possibilities but practitioners should be aware of this instability.

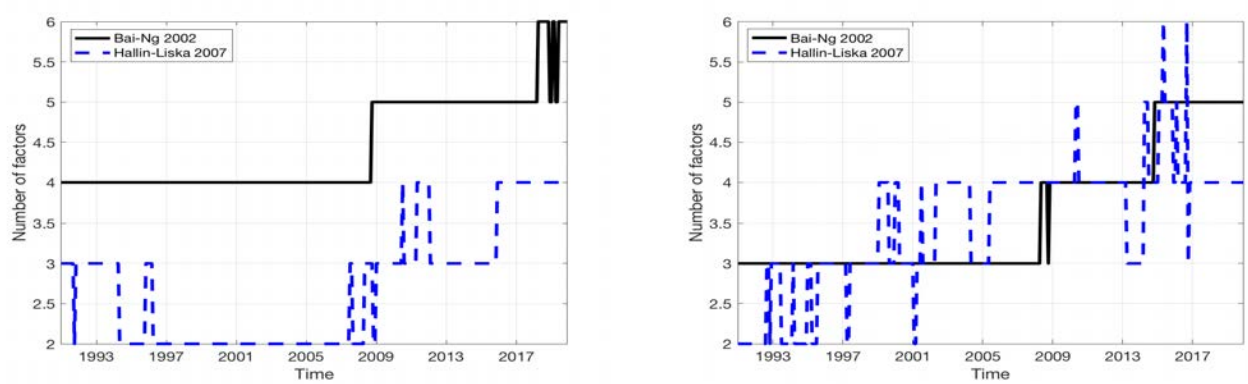
[8]These are the most commonly used procedures to select the numbers of static and dynamic factors respectively. We use the expanding window in the recursive procedure.

Figure 2: Eigenvalues and explanatory power of factors



Note: This figure plots the eigenvalues of the correlation matrix of data and the average explanatory power of consecutive factors.

Figure 3: Number of factors over time



(a) Canada (b) Canada + Provinces

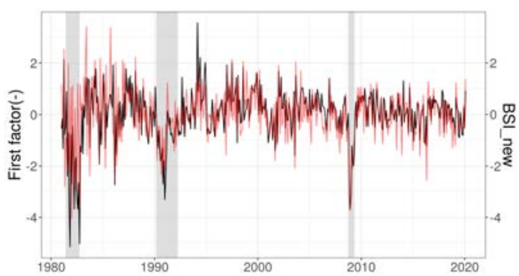
Note: This figure plots the number of factors selected recursively since 1981 by the Bai and Ng (2002) IC_{p2} information criterion and by the test of Hallin and Liska (2007).

2.3 Estimated Factors

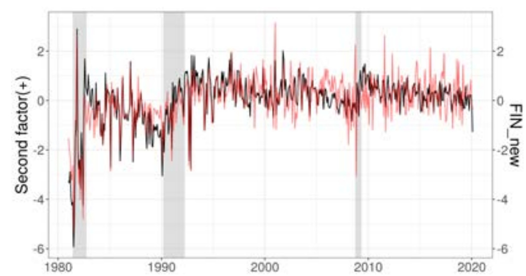
The factors estimated over the full sample by principal components are depicted in Figures 4 and 5 alongside their main series identified by the corresponding largest loading for each factor. The first factor closely tracks the evolution of real activity in Canada measured by GDP growth in the business sector, therefore capturing much of the movements related to business cycle frequencies.

The variable best explained by the second factor is the production in the finance, real estate and insurance sectors. The third factor is related to Treasury bonds of maturities 1-3 years, while the USD to CAD exchange rate movements seem to dominate the fourth factor. Another strong characteristic of the strength of the business cycle, unemployment average duration, is the most correlated variable with the fifth factor. The sixth factor is related to net flows in securities with US and the seventh to the spread between the 1-3Y Treasury bonds and the short-term bank rate. Finally, the Alberta oil production growth is driving the eighth factor. In addition to real activity variables, the importance of exchange rates, international transactions and oil production confirms the intuition that a small open economy business cycle should be heavily exposed to international markets. The stability of factors' interpretation is analyzed in section A.2 of the Appendix.

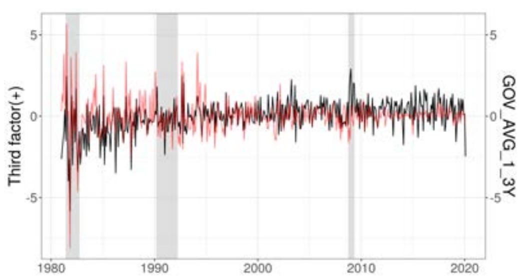
Figure 4: Factors 1 to 4 and their main series



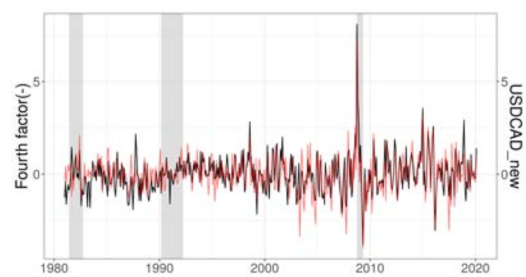
(a) Factor 1, GDP business



(b) Factor 2, GDP finance and insurance



(c) Factor 3, Governmental bonds 1-3 years



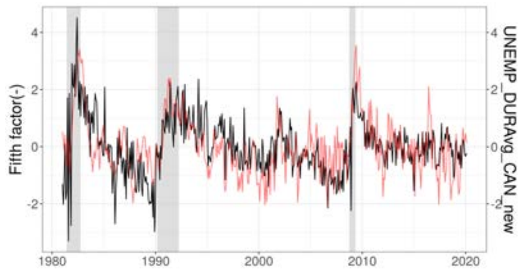
(d) Factor 4, Exchange rate CADUSD

Note: Factors are displayed in black and their main components in red. Factors have been estimated over the full sample and the chosen rotation is indicated by (+) or (-). Factors and series have been reduced by their respective standard deviation.

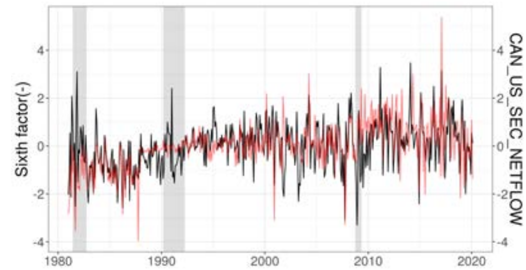
3 Predicting Recessions

In this section we verify the ability of the dataset in analyzing the Canadian business cycle. To begin, we need an operational definition of a recession. We assume peaks and troughs are observed and they coincide with the dates from Cross and Bergevin (2012). Since 1981, C.D. Howe committee has identified three recessions: June 1981 - October 1982, March 1990 - April 1992 and October 2008 - May 2009. Hence, these are fairly rare events in our dataset so we will not be

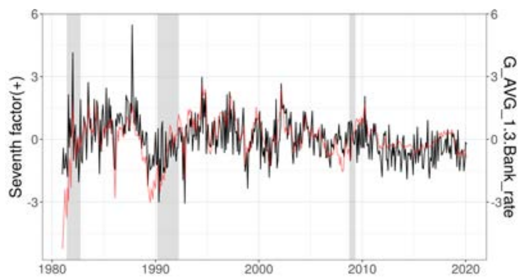
Figure 5: Factors 5 to 8 and their main series



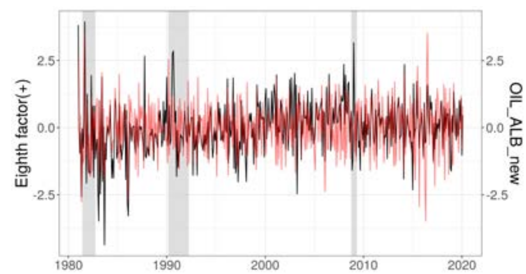
(a) Factor 5, Unemployment average duration



(b) Factor 6, Canadian securities, United States, Net flows



(c) Factor 7, Government bonds (1-3 years) - Bank rate



(d) Factor 8, Crude oil production in Alberta

Note: Factors are displayed in black and their main components in red. Factors have been estimated over the full sample and the chosen rotation is indicated by (+) or (-). Factors and series have been reduced by their respective standard deviation.

able to do a pseudo-out-of-sample forecasting evaluation. We will focus only on the in-sample capability to correctly identify the turning points and to discover important leading indicators of the business cycle.

We adopt the static Probit to model the probability of recession since this is the standard approach in the literature. Let $Z_{h,t}$ be a latent lead indicator:

$$Z_{h,t} = \alpha_h + \beta_h X_t + u_{h,t}, \tag{2}$$

where X_t is an N-dimensional predictors' set, $u_{h,t} \sim N(0,1)$, and which satisfies:

$$R_{t+h} = \left\{ \begin{array}{ll} 1 & \text{if } Z_{h,t} > 0 \\ 0 & \text{otherwise} \end{array} \right\}$$

where h is the forecasting horizon. Since Estrella and Mishkin (1998) it is standard practice to consider the slope of the yield curve as the only predictor. It is usually proxied by the term spread (TS) which is the difference between the 10-year and 3-month Treasury bills. This is our benchmark model. Therefore, the probability of recession is

$$\mathrm{P}(R_{t+h} = 1 | TS_t) = \Phi(\alpha_h + \beta_h TS_t). \tag{3}$$

Then, we consider two ways of including the information from our large macroeconomic dataset in predicting business cycle turning points. The first is the static Probit where instead of X_t we consider factors estimated as principal components of X_t:

$$Z_{h,t} = \alpha_h + \beta_h F_t + u_{h,t} \tag{4}$$
$$X_t = \Lambda F_t + e_t \tag{5}$$

The probability of recession is then

$$\mathrm{P}(R_{t+h} = 1 | F_t) = \Phi(\alpha_h + \beta_h F_t). \tag{6}$$

This is a two-step procedure. First, K principal components are constructed. Second, the Probit model is estimated with those K factors as inputs. Note that this is considered as *dense* modelling since all series in X_t are first used to construct $\hat{F}_t$.

Another popular way to include a large number of predictors is through a Lasso model. Following Sties (2017), we use the Logit Lasso model:

$$\mathrm{P}(R_{t+h} = 1 | X_t) = \frac{e^{(\alpha_h + \beta_h X_t)}}{1 + e^{(\alpha + \beta_h X_t)}}, \tag{7}$$

with

$$\underset{\alpha_h, \beta_h}{\arg\min} \left[RSS + \lambda \sum_{i=1}^{N} |\beta_{h,i}| \right].$$

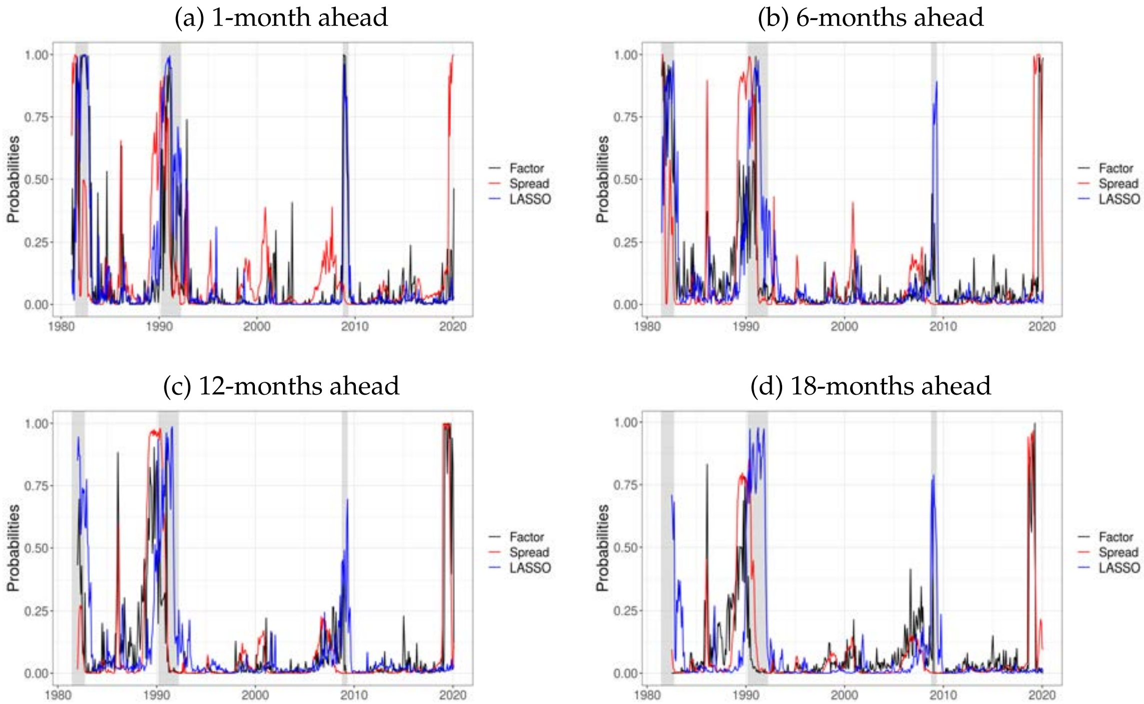
This is known as *sparse* modeling since many elements of β_h are set to zero. The hyperparameter λ is selected by cross-validation. As opposed to the factor Probit model (6), this is a one-step procedure.

Those three models are evaluated through the Estrella and McFadden pseudo-R^2s, the quadratic probability score (QPS), and the log probability score (LPS). The forecasting horizons are 1 to 18 months. Figure 6 shows the full-sample estimated probabilities for horizons 1, 6, 12 and 18 months ahead. Overall, all three models produce high probabilities during the C.D. Howe recession dates. Spread and factor Probit models produce more volatile probabilities and present a lot of 'false' signals.[9] Some of them are interpretable. The peak in 1987 is caused by the stock market crash, while the 2001 increase in recession probability reflects the U.S. recession. The increase at the end of sample is associated to the inversion of the term structure slope. On the other hand, the Lasso model probabilities are much smoother across all horizons.

Figure 7 shows goodness of fit measures across horizons for all three models. In terms of

[9] We call a false signal when the estimated probability is high while the C.D. Howe did not classify that observation as a recession. Of course, this false signal may also reveal some economic disturbances that were not pervasive or big enough to be judged as recession by the committee.

Figure 6: Predicting recessions: full sample probabilities



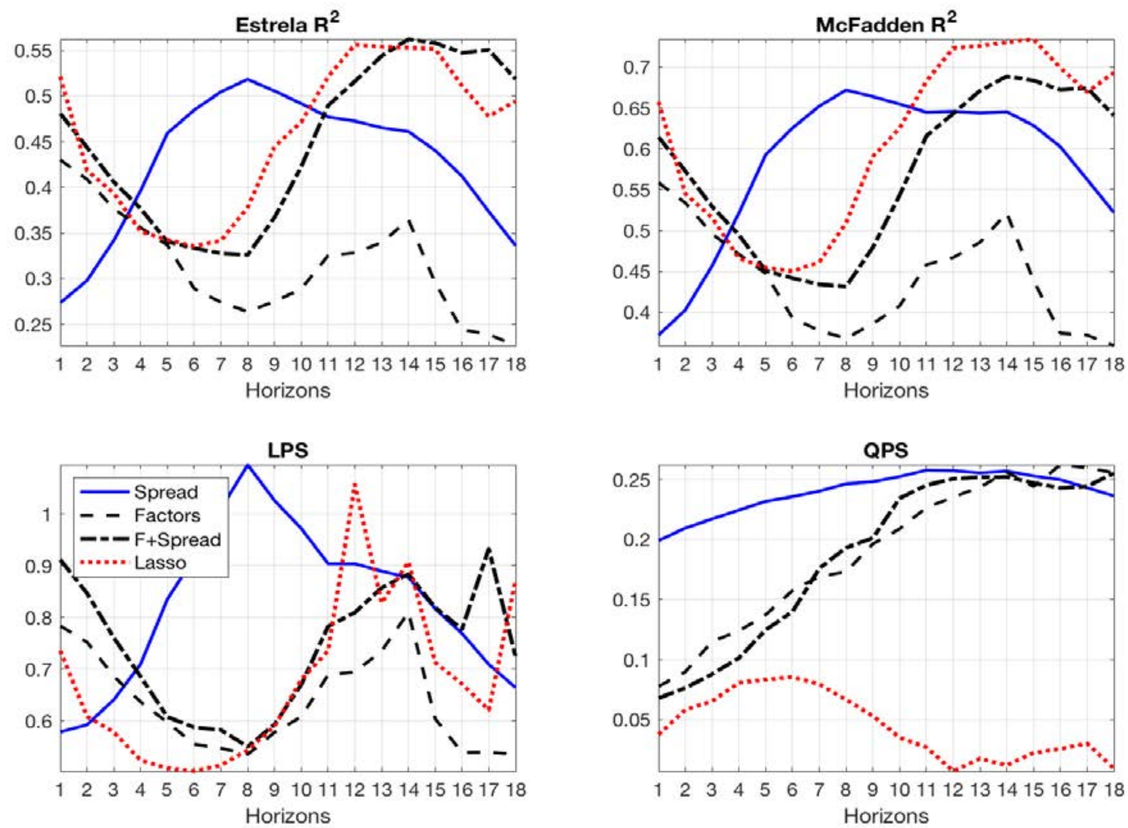
Note: This Figure reports the estimated probabilities of recessions from all three models and for horizons 1, 6, 12 and 18 months ahead. The shaded areas correspond to C.D. Howe recession dates.

pseudo-R^2, Spread model performance is maximized around 8-month ahead which has been already reported in the literature at least for US economy. Factors have better explanatory power at short horizons, while Lasso and the Spread model augmented by factors (F+Spread) improve at longer horizons. In terms of LPS and QPS, the Lasso model is preferred to the Probit alternatives, especially in case of the quadratic probability score.

Table 2 reports the 10 most important series of X_t selected by Lasso procedure for horizons 1, 6, 12 and 18 months ahead. One month ahead, the most important predictor is the initial claims, followed by a term spread and average unemployment duration. Employment and stock market indicators are also relevant. Claims and spreads are still the most important at 6-month horizon, and few price indices enter the top 10. As expected, spreads are the most decisive predictor at the 12 and 18-month horizons, followed by credit aggregates. Interestingly, the oil price arrives fourth at the longest horizon.

Overall, the analysis in this section shows that our dataset provides valuable information, compressed by factors or selected by Lasso, for monitoring the Canadian business cycle. In terms of individual predictors, we find that term spreads are very resilient, followed by the labor market and stock market indicators for short horizons, and credit aggregates for longer horizons.

Figure 7: Predicting recessions: goodness of fit



Note: This Figure shows several in-sample goodness-of-fit measures for all three models and for all horizons.

Table 2: Predicting recessions: top 10 series in Lasso

	h=1	h=6	h=12	h=18
1	CLAIMS_CAN	G_AVG_5.10.Bank_rate	G_AVG_5.10.Bank_rate	G_AVG_10p.TBILL_3M
2	G_AVG_5.10.Bank_rate	CLAIMS_CAN	CRED_MORT	CRED_HOUS
3	UNEMP_DURAvg_CAN_new	IPPI_MACH_CAN	TBILL_6M.Bank_rate	N_DUR_INV_RAT_new
4	TSX_CLO	TBILL_6M.Bank_rate	NHOUSE_P_CAN	WTISPLC
5	EMP_CAN	PC_3M.Bank_rate	RT_new	G_AVG_5.10.Bank_rate
6	TSX_HI	TSX_CLO	FIN_new	CLAIMS_CAN
7	BSI_new	PC_PAPER_1M	BANK_RATE_L	FOR_SEC_NETFLOW
8	NHOUSE_P_CAN	CPI_SERV_CAN	CPI_DUR_CAN	USDCAD_new
9	EMP_CONS_CAN	NHOUSE_P_CAN	GBPCAD_new	NHOUSE_P_CAN
10	PC_3M.Bank_rate	IPPI_METAL_CAN	RES_IMF	EMP_MANU_CAN

Note: This table reports 10 most important predictors selected by Lasso.

4 Forecasting Economic Activity

In order to explore the potential for predictive modelling of the CAN-MD database, we perform a standard out-of-sample forecasting exercise. Let Y_t be the variable of interest. If Y_t is stationary, the goal is to forecast its average over h periods:

$$y_{t+h}^{(h)} = (1200/h) \sum_{k=1}^{h} y_{t+k}, \tag{8}$$

where $y_t \equiv \ln Y_t$. If Y_t is an I(1) series, then we forecast the average annualized growth rate as in Stock and Watson (2002b) and McCracken and Ng (2016):

$$y_{t+h}^{(h)} = (1200/h) \ln(Y_{t+h}/Y_t). \tag{9}$$

4.1 Forecasting Models

A large number of forecasting techniques have been proposed to deal with big macroeconomic datasets, see Kotchoni et al. (2019) and Goulet-Coulombe et al. (2019) for a review and comparison. The goal of this section is to verify whether the CAN-MD dataset has some relevant and significant forecasting power in predicting key Canadian macroeconomic series, and not to find the best models. Therefore, we will use only a subset of data-rich methods based on dimension reduction, sparse modeling and model averaging.

Autoregressive Direct (ARD) The benchmark time series model is the *autoregressive direct* (ARD) model, which is specified as:

$$y_{t+h}^{(h)} = \alpha^{(h)} + \sum_{l=1}^{p_y^h} \rho_l^{(h)} y_{t-l+1} + e_{t+h}, \quad t = 1, \ldots, T, \tag{10}$$

where $y_t \equiv \ln Y_t - \ln Y_{t-1}$, $h \geq 1$ and $p_y^h < \infty$. A direct prediction of $y_{T+h}^{(h)}$ is deduced from the model above as follows:

$$\hat{y}_{T+h|T}^{(h)} = \hat{\alpha}^{(h)} + \sum_{l=1}^{p_y^h} \hat{\rho}_l^{(h)} y_{T-l+1},$$

where $\hat{\alpha}^{(h)}$ and $\hat{\rho}^{(h)}$ are OLS estimators of $\alpha^{(h)}$ and $\rho^{(h)}$. The optimal p_y^h is selected using the Bayesian Information Criterion (BIC).

Diffusion Indices (ARDI) The first data-rich model is the (direct) autoregression augmented with diffusion indices from Stock and Watson (2002b):

$$\begin{aligned} y_{t+h}^{(h)} &= \alpha^{(h)} + \sum_{l=1}^{p_y^h} \rho_l^{(h)} y_{t-l+1} + \sum_{l=1}^{p_f^h} F_{t-l+1} \beta_l^{(h)} + e_{t+h}, \quad t = 1, \ldots, T && (11) \\ X_t &= \Lambda F_t + u_t && (12) \end{aligned}$$

where X_t is the N-dimensional large informational set, F_t are $K^{(h)}$ static factors, and the superscript h stands for the value of K when forecasting h periods ahead. This the dimension-reduction workhorse model that has been heavily used for the macroeconomic forecasting. The optimal values of hyperparameters p_y^h, p_f^h, and $K^{(h)}$ are simultaneously selected by BIC from $1, \dots 6$ grids for the number of lags and $1, \dots 10$ for the number of factors. The h-step ahead forecast is obtained as:

$$\hat{y}_{T+h|T}^{(h)} = \hat{\alpha}^{(h)} + \sum_{l=1}^{p_y^h} \widehat{\rho}_l^{(h)} y_{T-l+1} + \sum_{l=1}^{p_f^h} F_{T-l+1} \widehat{\beta}_l^{(h)}.$$

The feasible ARDI model is obtained after estimating F_t as the first $K^{(h)}$ principal components of X_t.[10]

Penalized regressions An alternative shrinkage scheme to the factor model is the penalized regression:

$$\hat{\theta}_{Bridge} = \underset{\theta}{\operatorname{argmin}} \left\{ \sum_{t=1}^{T} \left(y_{t+h}^{(h)} - \sum_{i=1}^{N_Z} \theta_i Z_{it} \right)^2 + \lambda \sum_{i=1}^{N_Z} |\theta_i|^{\eta} \right\}, \; \eta > 0, \tag{13}$$

where $\lambda > 0$ is the hyperparameter controlling the strength of the regularization and Z_t is a collection of N_Z predictors from two distinct cases: (i) observables $Z_t := [\{y_{t-j}\}_{j=0}^{p_y}, \{X_{t-j}\}_{j=0}^{p_x}]$; (ii) ARDI $Z_t := [\{y_{t-j}\}_{j=0}^{p_y}, \{F_{t-j}\}_{j=0}^{p_f}]$.. We consider two special cases. If $\eta = 2$, (13) becomes the Ridge estimators (Hoerl and Kennard, 1970):

$$\hat{\theta}_{Ridge} = \left(Z'Z + \lambda I_{N_Z} \right)^{-1} Z'y, \tag{14}$$

where Z is the $T \times N_Z$ matrix of predictors, and y is the target vector. If $\eta = 1$, we obtain Lasso estimator (Least Absolute Shrinkage Selection Operator) of Tibshirani (1996)

$$\hat{\theta}_{Lasso} = \underset{\theta}{\operatorname{argmin}} \left\{ \sum_{t=1}^{T} \left(y_{t+h}^{(h)} - \sum_{i=1}^{N_Z} \theta_i Z_{it} \right)^2 + \lambda \sum_{i=1}^{N_Z} |\theta_i| \right\}. \tag{15}$$

Lasso is the representative of the *sparse* class of models where the predictive regression is estimated at the same time as variable selection is performed. In the presence of correlated predictors, Lasso tends to discard variables having less predictive impact, inducing an inconsistent model selection. Two solutions have been proposed. The first is the Elastic Net of Zou and Hastie (2004):

$$\hat{\theta}_{Elastic-Net} = \underset{\theta}{\operatorname{argmin}} \left\{ \sum_{t=1}^{T} \left(y_{t+h}^{(h)} - \sum_{i=1}^{N_Z} \theta_i Z_{it} \right)^2 + \lambda \sum_{i=1}^{N_Z} \left(\alpha |\theta_i| + (1-\alpha) \theta_i^2 \right) \right\}, \tag{16}$$

[10] See Stock and Watson (2002a) for technical details on the estimation of F_t as well as their asymptotic properties.

with $\alpha = [0, 1]$. Fixing α to 1 or 0 generates Lasso or Ridge respectively. The second alternative is the Adaptive Lasso of Zou and Hastie (2006):

$$\hat{\theta}_{Adaptive-Lasso} = \underset{\theta}{\text{argmin}} \left\{ \sum_{t=1}^{T} \left(y_{t+h}^{(h)} - \sum_{i=1}^{N_Z} \theta_i Z_{it} \right)^2 + \lambda \sum_{i=1}^{N_Z} \psi_i |\theta_i| \right\}, \tag{17}$$

where $\psi_i = \frac{1}{|\tilde{\theta}_i|^\gamma}$ are weights previously obtained from a consistent estimator $\tilde{\theta}_i$ and $\gamma > 0$. Here, $\tilde{\theta}_i$ is obtained by Ridge and we fix $\gamma = 1$. Hyperparameters λ and α are selected by cross-validation. The corresponding forecasting models are labelled by Ridge-X, Lasso-X, Elastic-Net-X, and Adaptive Lasso in the case of observable predictors, and ARDI, Ridge, ARDI, Lasso, ARDI, Elastic-Net, and ARDI,Adaptive-Lasso in the case of Z_t being populated by lags of y_t and estimated factors. In 'X' models, the number of lags are $p_y = p_x = 6$, while in factor space models we used $p_y = p_f = 6$ and $K = 10$ for every h.

Random forests The previous models are linear in both parameters and predictors. A growing literature on machine learning methods for macroeconomic forecasting is documenting the importance of nonlinearities, see Goulet-Coulombe et al. (2019) for details and review. One of the most promising, yet computationally feasible, methods to introduce nonlinearity in the predictive equation is to use regression trees.

The idea is to split sequentially the space of Z_t, as defined above, into several regions and model the response by the mean of $y_{t+h}^{(h)}$ in each region. The process continues according to some stopping rule. The details of the recursive algorithm can be found in Hastie et al. (2009). Then, the tree regression forecast has the following form:

$$\hat{f}(Z) = \sum_{m=1}^{M} c_m \mathrm{I}_{(Z \in R_m)}, \tag{18}$$

where M is the number of terminal nodes, c_m are node means, and $R_1, ..., R_M$ represents a partition of feature space. In the diffusion indices setup, the regression tree would estimate a nonlinear relationship linking factors and their lags to $y_{t+h}^{(h)}$. Once the tree structure is known, it can be related to a linear regression with dummy variables and their interactions.

However, the recursive tree fitting process is prone to overfitting. The most popular solution was proposed in Breiman (2001): Random Forests. This consists in growing many trees on subsamples (or nonparametric bootstrap samples) of observations. Further randomization of underlying trees is obtained by considering a random subset of regressors for each potential split. An important hyperparameter to be selected is the number of variables to be considered at each split, which is fixed to one third of the sample cross-section size. The minimum number of observations in every terminal node is set to 5. These are default values in Matlab. The forecasts of the estimated regression trees are then averaged together to make one single "ensemble" prediction of the targeted variable.[11] Depending on Z_t, two random forests models are used: RF-X (on observables) and RFARDI (on factors). The former has been successfully applied in Medeiros et al. (2019), while the RFARDI model has been one of the best models in Goulet-Coulombe et al. (2019).

Regularized Data-Rich Model Averaging Kotchoni et al. (2019) proposed a new class of data-rich model averaging techniques that combines pre-selection and regularization with the complete subset regressions (CSR) of Elliott et al. (2013). The idea of CSR is to generate a large number of predictions based on different subsets of X_t and then construct the final forecast as the simple average of the individual forecasts:

$$\hat{y}^{(h)}_{t+h,m} = c + \rho y_t + \beta X_{t,m} + \varepsilon_{t,m} \tag{19}$$

$$\hat{y}^{(h)}_{T+h|T} = \frac{\sum_{m=1}^{M} \hat{y}^{(h)}_{T+h|T,m}}{M} \tag{20}$$

where $X_{t,m}$ contains L series for each model $m = 1, \ldots, M$.

Kotchoni et al. (2019) proposed to preselect a subset of relevant predictors (first step) before applying the CSR algorithm (second step). This model is labelled Targeted CSR (**T-CSR**). The initial step is meant to discipline the behavior of the CSR algorithm ex ante. The idea is to pre-select a subset X^*_t of the series in X_t, that are relevant for forecasting $y^{(h)}_{t+h}$ as in Bai and Ng (2008). Then, CSR is applied on X^*_t. In particular, we use hard thresholding to construct X^*_t. A univariate predictive regression is done for each predictor X_{it}:

$$y^{(h)}_{t+h} = \alpha + \sum_{j=0}^{3} \rho_j y_{t-j} + \beta_i X_{i,t} + \epsilon_t. \tag{21}$$

The subset X^*_t is obtained by gathering those series whose coefficients β_i have the t-stat larger than the critical value t_c: $X^*_t = \{X_i \in X_t \mid t_{Xi} > t_c\}$, with $t_c = 1.65$. We consider T-CSR with three choices for the hyperparamter L: 5, 10, and 20 regressors, labelled T-CRS,5, T-CSR,10, and T-CSR,20 respectively. The total number of models is fixed at 2500.

4.2 Pseudo-Out-of-Sample Experiment Design

The pseudo-out-of-sample period is 1990:01 - 2019:12. The forecasting horizons considered are 1, 3, 6, and 12 months. All models are estimated with the expanding window. The results using the rolling window approach are reported in the appendix A.3. The hyperparameters are re-optimized every 24 months. When needed, 5-fold cross-validation is used. We consider the following variables: industrial production, employment, unemployment rate, consumer price index, core consumer price index, credit aggregates (total, business, and household), housing starts, and

[11] In this paper, we consider 500 trees, which is usually more than enough to get a stabilized prediction (that will not change with the addition of another tree).

building permits. These are typical macroeconomic aggregates that have been forecasted in the previous literature. All the series are modelled as I(1), hence we forecast the annualized growth rates. The forecasting performance of the above models will be compared on the basis of the Root Mean Square Prediction Error (RMSPE) as is often the case in forecasting literature. Other metrics could be used but for the sake of simplicity and under space constraints we stick to the most common one.

4.3 Results

Tables 3 - 6 summarize the results. We report the value of RMSPE ratio with respect to the reference ARD model as well as the p-value of Diebold-Mariano test. We group the variables in three categories: real activity (industrial production, employment, and unemployment rate), inflation (CPI and core CPI), credit market (total, business, and household), and housing market (housing starts, and house price).

Using our large database improves substantially the prediction power for real activity series. For instance, when forecasting industrial production one month ahead, almost all models outperform significantly the autoregressive reference and the winner is the random forest using all the observables, RF-X. For $h = 3$, improvements are even larger and the best model, Ridge-X, decreases the RMSE by 8%. At longer horizons, most of the models show significant ameliorations with ARDI estimated by Adaptive Lasso improving the accuracy by 15% at the one-year horizon. In the case of employment growth, ARDI,Elastic-Net is the best at short horizons. Interestingly, the forecasting power decreases at long horizons for this series. In the case of the unemployment rate, most of the models produce significantly better results than the autoregressive benchmark.

Table 3: Forecasting real activity

	Industrial Production				Employment				Unemployment			
Models	h=1	h=3	h=6	h=12	h=1	h=3	h=6	h=12	h=1	h=3	h=6	h=12
AR,BIC (RMSE)	0.010	0.006	0.005	0.004	0.002	0.001	0.001	<u>0.001</u>	0.186	0.109	0.088	0.073
ARDI,BIC	0.98**	0.94***	0.98	0.91*	0.97***	1.00	1.08*	1.31**	0.97*	0.93	0.91*	1.07
Elastic-Net-X	0.96***	0.94**	0.97	1.03	0.96**	0.98	1.14	1.42***	1.02	0.93*	0.99	1.20**
Ridge-X	0.95***	<u>0.92</u>**	0.91**	0.89**	0.96*	0.95	1.07	1.13	0.96***	0.90***	<u>0.89</u>**	1.00
Lasso-X	0.96***	0.94**	0.99	1.03	0.96**	0.98	1.11	1.42***	1.01	<u>0.88</u>***	0.96	1.21**
Adaptive-Lasso-X	0.98	0.96	0.98	1.04	0.96**	0.98	1.12	1.43***	0.99	0.91**	0.95	1.18*
RF-X	<u>0.94</u>***	0.95	0.96	0.94	0.95**	0.98	1.10	1.04	0.96***	0.91***	0.96	0.94
ARDI,Elastic-Net	0.95***	0.93**	<u>0.90</u>***	0.86**	<u>0.95</u>***	<u>0.93</u>**	1.12*	1.38***	0.97*	0.94	1.07	1.09
ARDI,Ridge	0.96**	0.94*	0.94**	0.87***	1.04	0.99	1.10*	1.21**	0.96***	0.93*	0.95	1.02
ARDI,Lasso	0.96***	0.94**	0.90***	0.86**	0.95***	0.94*	0.99	1.31**	0.96**	0.98	1.03	1.07
ARDI,Adaptive-Lasso	0.96***	0.94**	0.90**	<u>0.85</u>**	0.95***	0.94*	1.04	1.30**	0.96***	0.98	1.01	1.01
RFARDI	0.96***	0.95	0.94*	0.89***	0.95***	0.96	1.03	1.12**	<u>0.94</u>***	0.89***	0.90***	0.93*
T-CSR5	0.97***	0.94***	0.94***	0.90***	0.97***	0.95***	<u>0.98</u>	1.06	0.98**	0.92***	0.91***	<u>0.91</u>**
T-CSR10	0.97**	0.93***	0.94**	0.89**	0.97**	0.95**	1.00	1.16*	0.98	0.92***	0.91**	0.97
T-CSR20	0.99	0.94**	0.96	0.93*	0.98	0.97	1.05	1.32**	1.00	0.94**	0.95	1.10

Note: This table reports the ratio of the root mean squared predictive error (RMSPE) with respect to the reference ARD model and the results of the Diebold-Mariano test with *10%, **5%, ***1%.

Table 4 shows that using the large panel greatly improves the prediction of inflation series. RF-X is in general the most resilient model which is in line with Medeiros et al. (2019). Probably the most important horizon when forecasting inflation is the one year ahead and the regularized data-rich averaging model T-CSR outperforms the autoregressive benchmark by 24 and 13% for total and core inflation respectively.

Table 4: Forecasting inflation

Models	CPI				Core CPI			
	h=1	h=3	h=6	h=12	h=1	h=3	h=6	h=12
AR,BIC (RMSE)	0.004	0.003	0.002	0.001	0.003	0.002	0.001	0.001
ARDI,BIC	0.98	0.93***	0.86***	0.81***	1.00	0.95	0.95	0.96
Elastic-Net-X	0.93***	0.91***	0.85***	0.84**	0.92***	0.93**	0.91**	0.92
Ridge-X	0.95***	0.90***	0.85***	0.83***	0.96**	0.93**	0.92**	1.04
Lasso-X	0.94***	0.91***	0.86***	0.79***	0.94***	0.94*	0.92**	0.88*
Adaptive-Lasso-X	0.94***	0.92***	0.85***	0.79***	0.93***	0.92**	0.91**	0.88
RF-X	0.93***	0.88***	0.86***	0.92	0.91***	0.86***	0.89***	0.95
ARDI,Elastic-Net	0.98**	0.95*	0.90**	0.84**	0.98	0.98	0.97	0.97
ARDI,Ridge	0.98	0.94**	0.90**	1.01	0.99	1.02	0.98	1.06
ARDI,Lasso	0.99	0.91***	0.84***	0.79***	0.97*	0.95**	0.92**	0.90
ARDI,Adaptive-Lasso	0.97**	0.91***	0.84***	0.79***	0.98	0.94*	0.90**	0.91
RFARDI	0.95***	0.89***	0.82***	0.88**	0.95***	0.91***	0.89***	1.03
T-CSR5	0.95***	0.92***	0.87***	0.87***	0.96***	0.97**	0.96**	0.97
T-CSR10	0.94***	0.91***	0.83***	0.79***	0.95***	0.94***	0.92**	0.91*
T-CSR20	0.95**	0.92***	0.86***	0.76***	0.97	0.94**	0.92**	0.87**

Note: See table 3.

The results for the credit market, presented in the table 5, are mixed. In the case of total credit growth, the best models are RFARDI and T-CSR, but improvements are small and insignificant. T-CSR10 ameliorates substantially forecasting power for the business credit at horizons 6 and 12, by as much as 8 and 11% respectively.

Table 5: Forecasting credit markets

Models	Total Credit				Business Credit				Consumption Credit			
	h=1	h=3	h=6	h=12	h=1	h=3	h=6	h=12	h=1	h=3	h=6	h=12
AR,BIC (RMSE)	0.002	0.001	0.001	0.002	0.003	0.002	0.002	0.002	0.003	0.002	0.002	0.002
ARDI,BIC	1.04**	1.08**	1.11**	1.20***	1.01	1.00	1.00	1.00	1.05***	1.09**	1.13**	1.27***
Elastic-Net-X	1.01	1.04	1.13**	1.13**	1.03	1.01	1.02	1.08	1.11***	1.18***	1.22***	1.34***
Ridge-X	1.14***	1.19***	1.24***	1.28***	1.08**	1.13***	1.16***	1.08	1.21***	1.26***	1.34***	1.27***
Lasso-X	1.04*	1.03	1.14***	1.15**	1.04**	1.01	1.03	1.07	1.12***	1.18***	1.22***	1.33***
Adaptive-Lasso-X	1.02	1.03	1.13**	1.15**	1.04*	1.01	1.01	1.07	1.11***	1.20***	1.25***	1.32***
RF-X	1.02	1.14***	1.27***	1.27***	1.04**	1.13***	1.23***	1.21***	1.03	1.09**	1.19***	1.25***
ARDI,Elastic-Net	1.03	1.08*	1.10*	1.13*	1.02	1.00	1.00	0.96	1.07***	1.08*	1.13**	1.23***
ARDI,Ridge	1.19***	1.25***	1.36***	1.15**	1.10***	1.08*	1.09	1.12**	1.17***	1.25***	1.25***	1.26***
ARDI,Lasso	1.00	1.02	1.03	1.08	1.02	0.97	0.97	0.96	1.07***	1.10**	1.18**	1.23***
ARDI,Adaptive-Lasso	1.00	1.02	1.03	1.08	1.02	0.98	0.96	0.96	1.07***	1.10**	1.17**	1.24***
RFARDI	0.99	1.04	1.10**	1.11**	1.02	1.04*	1.10**	1.10**	1.02	1.01	1.05	1.08*
T-CSR5	1.00	0.98	0.99	1.00	1.00	0.98	0.93**	0.90**	1.00	0.99	1.01	1.05
T-CSR10	1.02	0.97	1.01	1.04	1.02	0.98	0.92**	0.89**	1.02	1.02	1.05	1.11**
T-CSR20	1.07***	0.99	1.04	1.11*	1.07***	1.01	0.94*	0.91*	1.07**	1.06*	1.12**	1.19**

Note: See table 3.

Finally, table 6 reports the results for the housing market. It shows that predicting housing starts and building permits growths is a very difficult task. Virtually none of our models improves significantly upon the autoregressive benchmark.

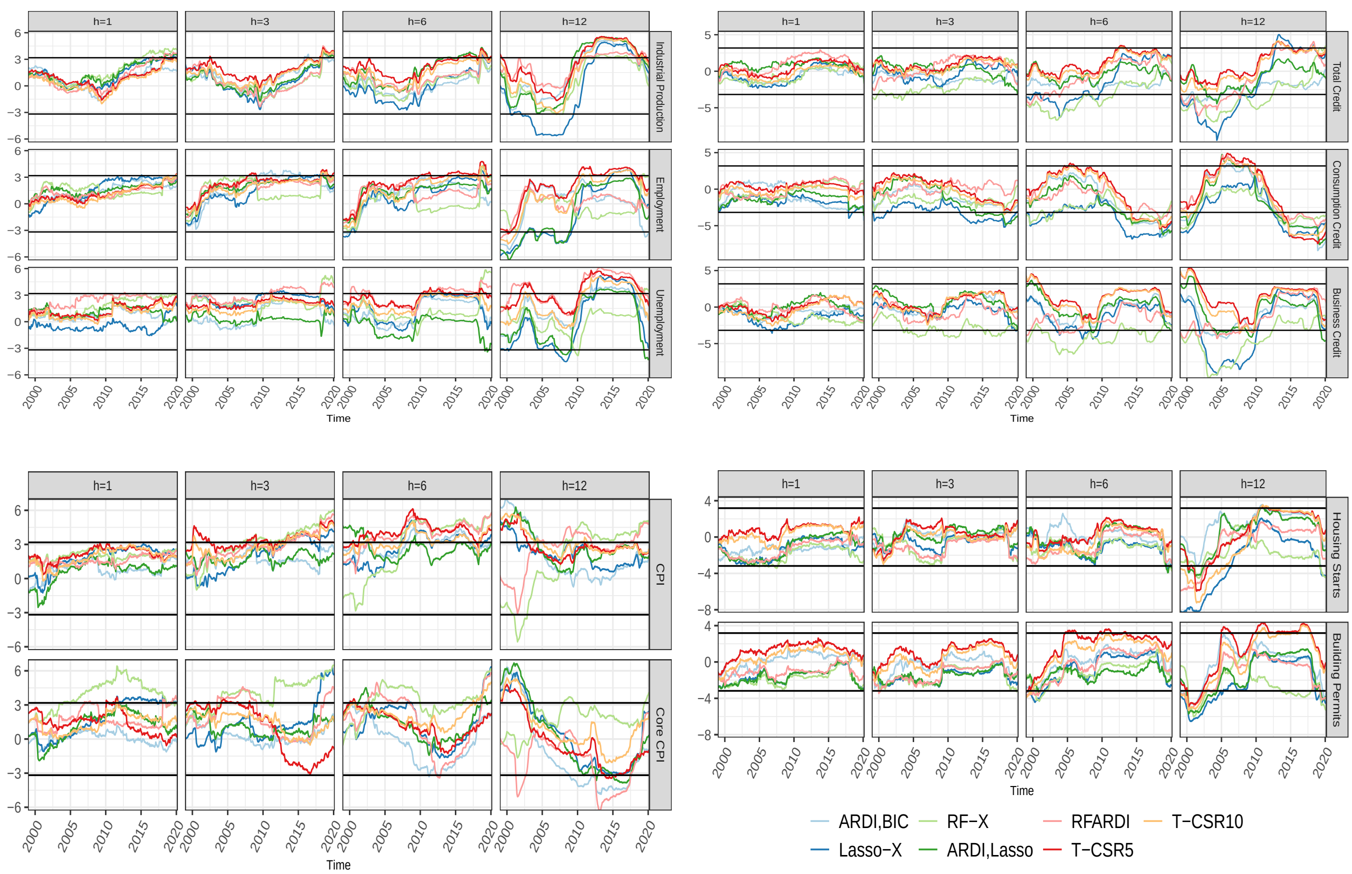
Table 6: Forecasting the housing market

Models	Housing Starts				Building Permits			
	h=1	h=3	h=6	h=12	h=1	h=3	h=6	h=12
AR,BIC (RMSE)	0.090	0.040	0.026	0.017	0.079	0.032	0.020	0.013
ARDI,BIC	1.00***	1.00	0.99	0.96	1.00	1.02	1.02*	1.11**
Elastic-Net-X	1.04**	1.03	1.05***	1.21***	1.05***	1.04**	1.07**	1.16**
Ridge-X	1.06***	1.01	1.01	1.04	1.07***	1.06***	1.04**	1.09
Lasso-X	1.02*	1.01	1.02*	1.16***	1.04***	1.04**	1.07**	1.17**
Adaptive-Lasso-X	1.02*	1.03**	1.03**	1.16***	1.04***	1.05***	1.05**	1.26***
RF-X	1.04***	1.01	1.03***	1.06**	1.04***	1.04*	1.06	1.05
ARDI,Elastic-Net	1.03**	1.02	0.99	0.99	1.04***	1.05***	1.07***	1.09
ARDI,Ridge	1.05***	1.01	1.00	1.02	1.07***	1.05***	1.04**	1.04*
ARDI,Lasso	1.01*	1.00	1.00	1.00	1.04***	1.03**	1.03***	1.09
ARDI,Adaptive-Lasso	1.02***	1.02*	1.00	1.00	1.03***	1.05***	1.02**	1.11
RFARDI	1.03***	1.02*	1.04*	1.07**	1.03**	1.04**	1.06**	1.08**
T-CSR5	0.99	1.00	1.00	0.99	0.99	1.01	1.03	1.04
T-CSR10	1.00	1.01	1.03	1.05	1.00	1.03	1.07*	1.11*
T-CSR20	1.04*	1.04*	1.09**	1.19***	1.04**	1.07*	1.18**	1.25**

Note: See table 3.

Up to now we have studied the average performance over the whole 1990-2019 period. Giacomini and Rossi (2010) propose a test to compare the out-of-sample forecasting performance of two competing models in the presence of instabilities. Figure 8 shows the results. We report the comparison between selected data-rich models and the autoregressive benchmark. Following the Monte Carlo results in Giacomini and Rossi (2010), the moving average of the standardized difference of MSPEs is produced with a window that uses 30% of the out-of-sample period. The critical value of 10% is used. Positive values of the test statistic reflect a better performance of a competing model, which becomes significant if above the critical value. For real activity series, the performance is relatively stable across horizons and variables. For industrial production, there is a ditch in the performance around 2005 but it fully recovers by the end of the sample. In the case of inflation, the forecasting power generally improves over time except for the core inflation at one-year horizon. The fluctuation test is quite stable for credit markets at short horizons but indicate a lot of instability when predicting housing starts and building permits.

Figure 8: Forecasting performance over time: fluctuation test



Note: The figure shows the Giacomini-Rossi fluctuation test for best RMSPE models against the ARD benchmark. Solide lines correspond to 10% critical value.

In the above analysis the expanding window approach has been used, which is less robust to frequent structural breaks, but more efficient since more observations are available to estimate the parameters. When the rolling window is used, we find relatively similar results except that the distribution of best models by variable and horizon is different. For instance, the standard ARDI is in general the most resilient model when predicting real activity variables. In case of credit markets, the T-CSR5 model improves significantly the predictive accuracy for most of the horizons and variables. The results are available in tables 11-14 and in figure 15.

Our monthly and quarterly datasets have already been successfully used in other forecasting exercises. Goulet-Coulombe et al. (2019) have shown that machine learning methods relying on (nonparametric) nonlinearities can improve the forecasting accuracy of Canadian macroeconomic variables when paired with large datasets such as CAN-MD and CAN-QD.

5 Measuring heterogenous effects of monetary policy

In this section we take advantage of the richness of the cross section of CAN-MD database to study the regional and sectoral effects of monetary policy.[12] The Bank of Canada's goal of economic stabilization throughout Canada is not equivalent to economic stability in all of Canada's provinces at the same time. This can be an issue in all monetary unions; a cure for the union can become a curse for some of its members if their business cycles are not synchronized (Micossi, 2015). Our goal in this section is not to introduce new estimation methodologies but to show how CAN-MD can be used to explore regional and sectoral effects of shocks on key macroeconomic aggregates and their components.[13]

To estimate the impulse response functions (IRFs) of key macroeconomic variables to monetary policy shocks we follow Champagne and Sekkel (2018) and use local projections with their constructed monetary policy shocks.[14] Their shock is constructed following the narrative approach of Romer and Romer (2004) that uses the monetary policy framework to decompose rate changes in systematic and exogenous components. Each rate change is composed of the Bank of Canada's systematic reaction function to current and expected economic conditions and of the monetary policy shocks. To identify the latter, Champagne and Sekkel (2018) use real-time information available during meetings of the Governing Council preceding the interest rate an-

[12]Note that our CAN-MD and CAN-QD datasets have been recently used in Moran et al. (2021) who constructed a measure of Canadian macroeconomic uncertainty and studied their effects in the context of Covid-19 pandemic.

[13]The study of the regional effects of monetary policy has a long history. Dominguez-Torres and Hierro (2019) provide a thorough review of the literature. Kronick and Ambler (2019) estimate regional effects of monetary policy shocks but only on inflation and unemployment. We go further by considering the components of inflation, the housing market, and sectoral employment.

[14]See Dufour and Renault (1998), Jordà (2005), and Plagborg-Møller and Wolf (2020) for details on local projections as means of estimating IRFs. We opted for a direct approach via local projections instead of the simultaneous approach like a Factor-Augmented VAR as in Bernanke et al. (2005) because the structural shock here is already identified and hence considered as an exogenous variable. The alternative would be to add ϵ_t as an exogenous variable in the VAR process specified on the above control variables. Here, given a very large number of provincial variables (hence correlation clusters that can affect the estimation of common factors, (Boivin and Ng, 2006)) we prefer to estimate IRFs with a direct approach and not impose factor model restrictions (Stevanovic, 2015).

nouncement to purge the rate changes of the systematic component.

We estimate IRFs for price, labor market, and housing market series for Canada, Ontario, Québec, Manitoba, Saskatchewan, British Columbia, Alberta, New Brunswick, Nova Scotia, and Newfoundland.[15] Table 7 lists the selected series. These variables are among key indicators for the conduct of the monetary policy in Canada and are available for provinces.

Table 7: Variables of interest for the impulse response analysis

Prices	Labor market	Housing market
CPI_total	Total_EMP	Build_permit_total
CPI_core	Services_EMP	Build_permit_ind
CPI_goods	Resources_EMP	Build_permit_comm
CPI_services	Const_EMP	Housing_start
CPI_durables	Sales_EMP	
CPI_health	Finance_EMP	
CPI_clothing	Manufacturing_EMP	
CPI_shelter	Unemployment	

Note: IRFs of these series are estimated for Canada and all provinces but Prince Edward Island.

For all provinces p and all series s we estimate the following regressions:

$$x_{t+h,s,p} - x_{t,s,p} = c_{h,s,p} + \Phi_{h,s,p}(L)Z_{t-1,s,p} + \beta_{h,s,p}\epsilon_t + v_{t+h,s,p}, \tag{22}$$

where $x_{t,s,p}$ denotes the variable of interest as listed in Table 7, $Z_{t-1,s,p}$ contains control variables, ϵ_t is the already identified monetary policy shock series, and $h = 0, 1, ..., 48$. We follow closely Champagne and Sekkel (2018) in the variables used as controls in $Z_{t-1,s,p}$; when estimating the IRFs for Canada we include real GDP growth rate, CPI growth rate, and the growth rate of series s, monetary policy shock lags but instead of using the growth rate of commodity prices as they do we instead include the first four principal components extracted from CAN-MD.[16] When estimating the IRFs of provinces, we use the same controls as for Canada but augment the set with the core CPI inflation rate and unemployment rate of the province p to capture provincial business cycles. In all cases we use 4 lags of control variables and 48 lags of the monetary policy shocks. The full sample time span is 1981M01 - 2015M10 and we also consider the estimation during the inflation targeting (IT) period that starts in 1992M01. Given a limited number of observations and a large number of lags in controls, we do not consider estimating (22) during the pre-IT period only. $\beta_{s,h,p}$ is then the effect of the monetary policy shocks h months ahead, for series s and province p.

There is a fair amount of heterogeneity across regions, sectors, and time and thus we choose to resume and quantify the main sources of heterogeneity in IRFs with the following fixed effect

[15] Prince Edward Island is left out of this analysis since some of the series considered were problematic.

[16] Bernanke et al. (2005) show that using principal components can solve the price puzzle found on US data without having to rely on commodity prices as an ad hoc way of correcting the puzzle. Boivin et al. (2010) apply a similar approach on Canadian data and also find that it solves many puzzles found in the literature as it better approximates the Central Bank's information set.

model:

$$\hat{\beta}_{h,s,p} - \hat{\beta}_{h,s,C} = c + \theta_{h,p} + \phi_{h,s} + e_{h,s,p}, \tag{23}$$

where the left hand side is the gap between province's p estimated IRFs for series s at a given horizon h ($\hat{\beta}_{h,s,p}$) and the same series for Canada ($\hat{\beta}_{h,s,C}$), while $\theta_{h,p}$ and $\phi_{h,s}$ are the provincial and series fixed effects.[17] Figure 9 shows the results in terms of explained heterogeneity for both full sample and IT period using the R^2 from the fixed-effect regressions.

Results of the first column (All series) come from the estimation of equation (23) using the IRFs of all series from Table 7, i.e. all sectors (prices, labor, and housing), all their components (or subsectors) and for all provinces. The second (Aggregate series) performs the same analysis using only the IRFs for core CPI, unemployment, total employment, housing starts, and total building permits, hence the component-specific variation is averaged out. In the former case, the sectorial (and component-specific) source of heterogeneity in IRFs are more important than regional ones. The total R^2 rises slightly since the inflation targeting shift in the monetary policy. When only aggregate variables are used, the picture is similar for the full sample, but for the IT-period we observe that regional heterogeneity becomes more important within two years after the shock.

To investigate this heterogeneity at a more granular level, we perform the same analysis on employment and price series' IRFs separately. The results are reported in the third and fourth columns respectively. Those graphs reveal that provincial unobserved heterogeneity is the most important ingredient to explain the gaps in IRFs. Comparing full sample and inflation targeting periods shows that the importance of both sources of heterogeneity has decreased with the change in monetary policy, which could be interpreted as a result of monetary policy effectiveness to stabilize the economy and to synchronize the business cycle fluctuations across the country (Mihov, 2001; Boivin and Giannoni, 2006).

We now explore the average differences for employment and CPI series in separate analysis. In other words, for every group of series formed from employment sub-sectors and CPI subcomponents, we estimate the following fixed-effect model

$$\hat{\beta}_{h,s,p} = \Phi^{CAN}_{h,Bench.} + \theta_{h,p} + \phi_{h,s} + e_{h,s,p}, \tag{24}$$

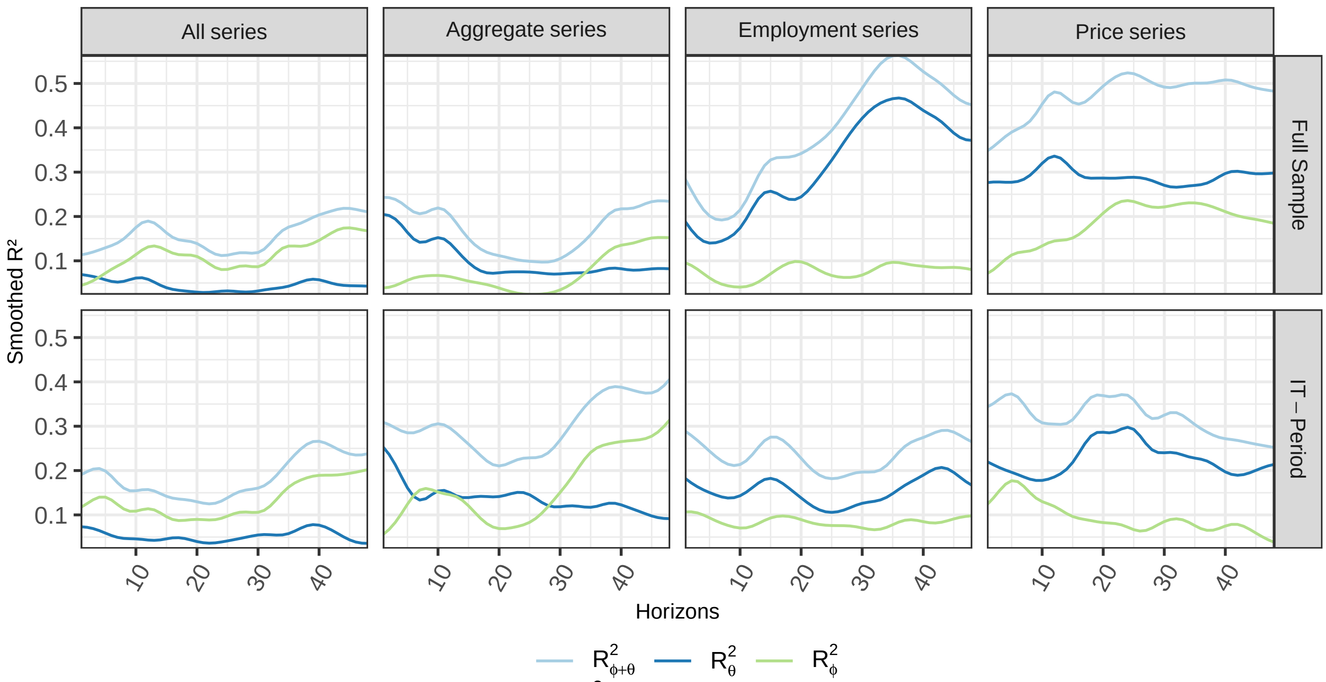
where $\Phi^{CAN}_{h,Bench.}$ is the IRF of either Canadian total employment or Core CPI, while $\theta_{h,p}$ and $\phi_{h,s}$ are the province and sub-sector (sub-component) h-specific fixed effects.

Figure 10 shows the estimated fixed effects coefficients for sectorial employment and CPI components for Canada and across provinces.[18] This figure reports the IRFs of the benchmark in the leftmost column and fixed effect estimates $\hat{\theta}_{h,p}$ and $\hat{\phi}_{h,s}$ thereafter. For example, let's look at the

[17] Selected IRFs are reported in the appendix A.4.

[18] Dedola and Lippi (2005) and Peersman and Smets (2005) have documented cross-industry heterogeneities to monetary policy shocks using industrial output in France, Germany, Italy, the UK, the US, and the Euro zone, while Farès and Srour (2001) have explored the cross-industry heterogeneity for Canada.

Figure 9: Total heterogeneity explained by sectors and provinces



Note: The light blue line show the total smoothed R^2 from equation (23) while the dark blue and green lines respectively show the smoothed R^2 using only provincial and sectorial fixed effects.

leftmost two entries in the top panel: the IRF of total employment in Canada $\hat{\phi}^{CAN}_{h,Total}$ and the fixed effects associated with the response of employment in the service industry $\hat{\phi}_{h,Service}$. The average response of service employment is also negative since the sum of $\hat{\phi}^{CAN}_{h,Total} < 0$ and $\hat{\phi}_{h,Service} \simeq 0$ is negative. The same panel also reveals that the response has the same sign and is much stronger in the Atlantic provinces ($\hat{\theta}_{NF}, \hat{\theta}_{NS}, \hat{\theta}_{NB} \ll 0$) and that it eventually turns positive in the Prairies ($\hat{\theta}_{MB}, \hat{\theta}_{SK}, \hat{\theta}_{AB} \gg 0$ at longer horizons).

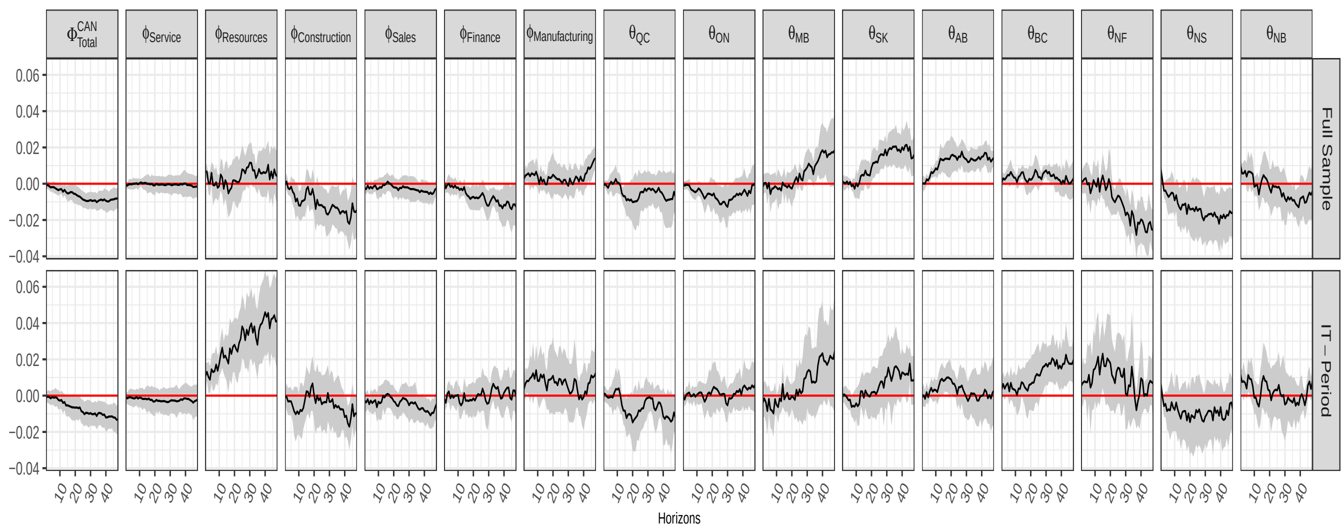
In the case of employment for the full sample, we remark that the construction sector respond more to monetary policy shocks than total employment, as well as Ontario, Québec, and few Atlantic provinces, while the opposite is true for the west part of Canada with smaller and less persistent responses of employment. Since 1992, the heterogeneity across provinces and sectors is dampened, except for employment in the resource sector which exhibits a clear increase over the entire IRF horizon. These results are broadly in line with Jansen et al. (2013) who find that firms in the construction sector in the US are more affected by changes in interest rates while those in the mining sector are better off following a tightening of monetary policy.

The second part of figure 10 explores regional and sectorial heterogeneity in the response of prices. In the full sample, the responses to monetary policy shocks for most provinces are weaker than for Canada, while Ontario is more affected. In terms of sub-components, the heterogeneity is mostly observed in durable goods which virtually do not respond with $\hat{\phi}_{Durables}$ going the opposite direction of $\hat{\Phi}^{CAN}_{Core}$. After the change in monetary policy in 1992, the regional differences are much smaller and the response for durable goods is even less important. This lower response of durable good prices is consistent with the idea that their consumption is highly interest rate sensitive and has a central role in monetary policy transmission (Erceg and Levin, 2006; Barsky et al., 2007; Cantelmo and Melina, 2018).

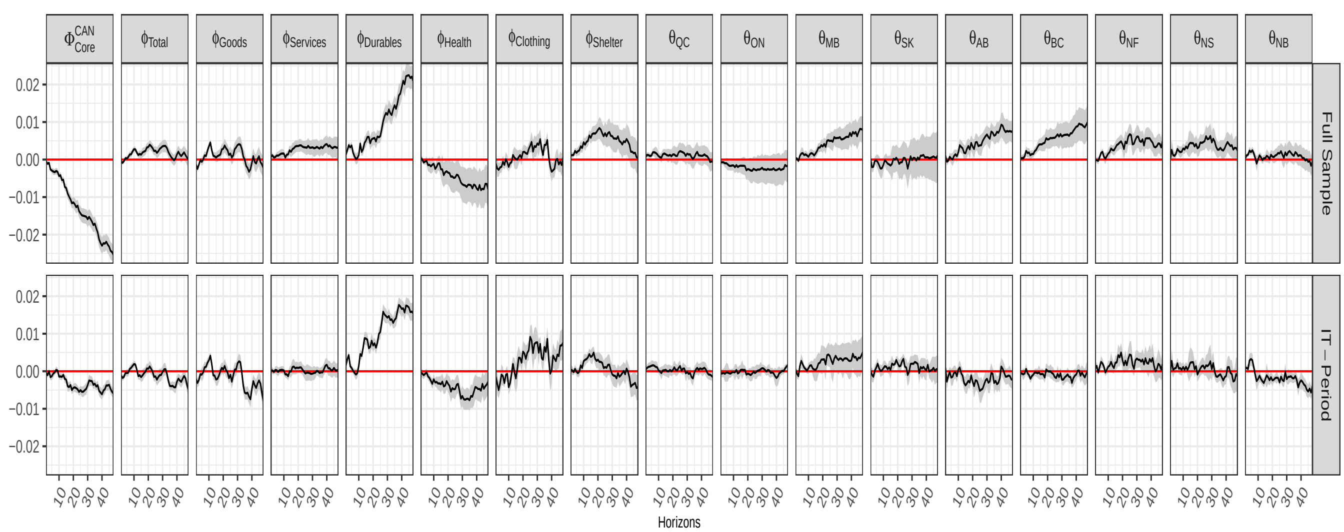
Overall, this analysis has documented a presence of a fair amount of heterogeneity across sectors, regions, and time in the effects and transmission of the monetary policy in Canada. If inflation targeting has helped to decrease those differences, still some regional heterogeneity pertains and may pose a challenge for the Bank of Canada in its role to further stabilize the economy.

Figure 10: Heterogeneity across sectors and provinces

(a) Employment



(b) Inflation



Note: This figure shows the estimated fixed effect coefficients from equation (24) along with the 90% confidence bands constructed using heteroskedastic consistent standard errors.

6 Conclusion

In this paper we proposed a large-scale Canadian macroeconomic database containing hundreds of Canadian and provincial economic indicators. It is designed to be updated regularly through the StatCan database and is publicly available. Real-time vintages are collected as well. It relieves users from dealing with data changes and methodological revisions and we provide an already balanced and stationary panel starting in 1981.

Four important features of the dataset have been explored. First, we studied the factor structure and found that common factors explain a sizable portion of variation in Canadian and provincial aggregate series. Few driving forces of the Canadian economy have been identified, such as GDP in business and financial sectors, term structure, exchange rates, unemployment duration, and international transaction net flows and oil production. Second, the dataset has been applied to the prediction of turning points for the Canadian business cycle. Using Probit, Lasso, and factor models we showed that this dataset has substantial explanatory power in addition to the standard term spread predictor.

Third, using the dataset has substantially improved the predictive accuracy when forecasting key real macroeconomic indicators. Factor and sparse models, random forests, and regularized complete subset regressions showed good performance in forecasting real activity variables such as industrial production, employment and unemployment rate, as well as CPI and Core CPI inflation.

Finally, we studied heterogenous effects of monetary policy on different sectors of the Canadian economy and across regions. Results suggested that the passage to inflation targeting since 1992 coincides with a decrease in those differences, but some regional heterogeneity still pertains and may pose a challenge for the Bank of Canada in its role to further stabilize the economy.

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A ONLINE APPENDIX - Additional results

A.1 Seasonal adjustments

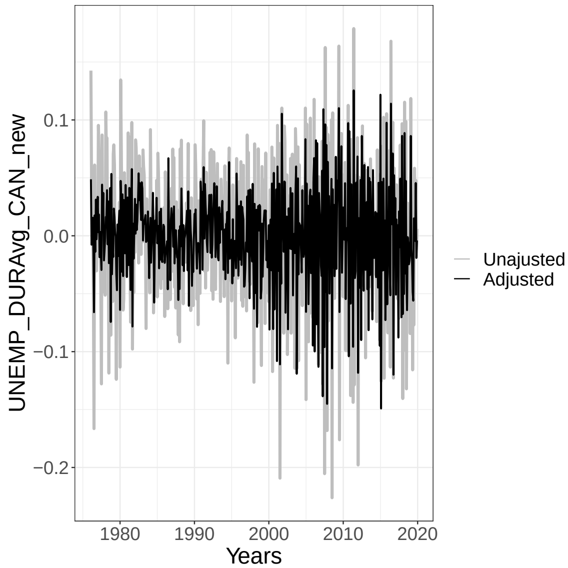
The series under investigation is split into 12 subsamples, each consisting of $(\tau_j)_{j=1}^{12}$ observations specific to a given month. Under the null hypothesis of no seasonal behavior, these subsamples must have the same mean. The Kruskal-Wallis test (Kruskal and Wallis (1952)) offers a non-parametric approach to test this hypothesis. In each subsample, observations are assigned a rank R_{ij} following their relative magnitudes. If T is the total number of observations, the Kruskal-Wallis statistic is given by:

$$KW = \frac{12}{T(T+1)} \sum_{j=1}^{12} \tau_j \left(\frac{\sum_{i=1}^{\tau_j} R_{ij}}{\tau_j} \right)^2 - 3(T+1) \overset{approx.}{\sim} \chi^2(12-1). \tag{25}$$

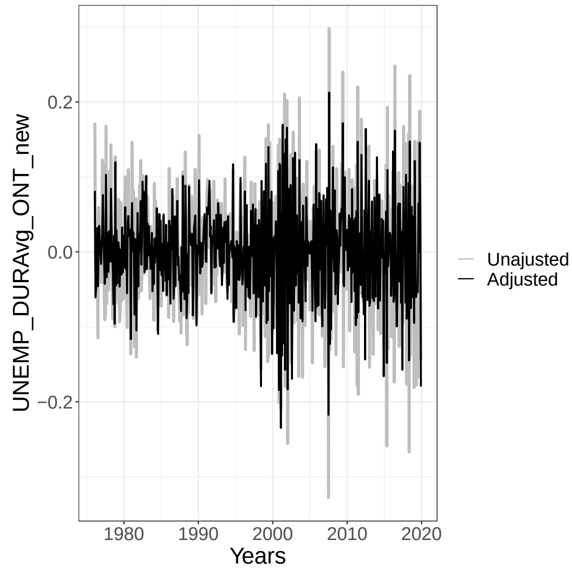
Table 8: Kruskal-Wallis Rank Sum Test Results

Series	Unajusted		Ajusted	
	chi-squared	p-value	chi-squared	p-value
Unemployment duration				
Canada	239.6419	0	0.8426	1
New Foundland	57.6381	0	1.9380	0.9987
Prince Edward Island	216.5544	0	1.7885	0.9991
Nova Scotia	131.6689	0	1.9556	0.9986
New Brunswick	75.7492	0	1.4571	0.9997
Quebec	76.0553	0	0.9038	1
Ontario	171.9024	0	0.3691	1
Manitoba	74.1367	0	0.8112	1
Saskatchewan	93.2069	0	2.2827	0.9972
Alberta	92.7645	0	3.5774	0.9807
British Columbia	87.9181	0	0.9468	1
Initial claims				
Canada	309.4079	0	0.6171	1
New Foundland	387.0221	0	0.8858	1
Prince Edward Island	416.8684	0	0.5220	1
Nova Scotia	382.3249	0	0.3162	1
New Brunswick	425.1459	0	0.3084	1
Quebec	317.1152	0	1.8707	0.9989
Ontario	254.3162	0	0.4762	1
Manitoba	279.2051	0	0.3161	1
Saskatchewan	288.7726	0	0.5814	1
Alberta	74.4530	0	0.3275	1
British Columbia	213.2004	0	0.7640	1

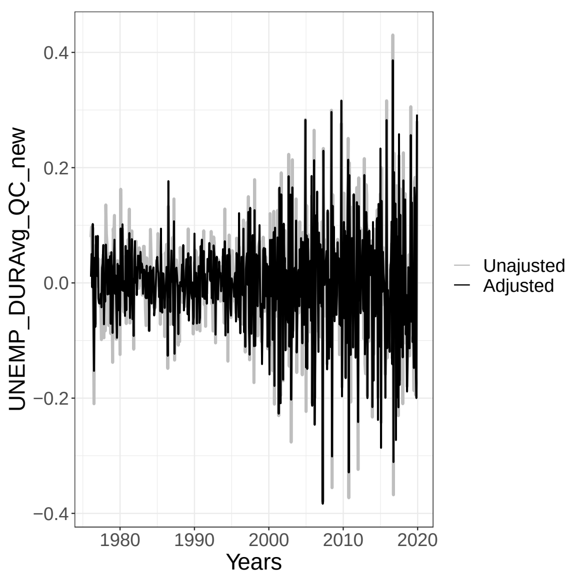
Figure 11: Seasonal adjustment of unemployment duration



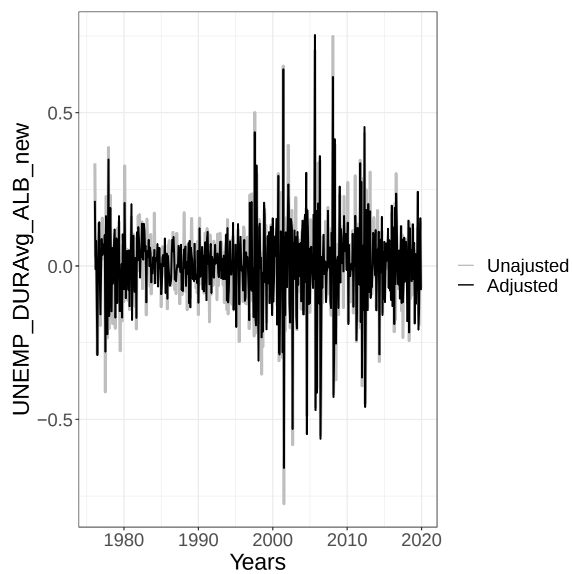
(a) Canada



(b) Ontario



(c) Québec



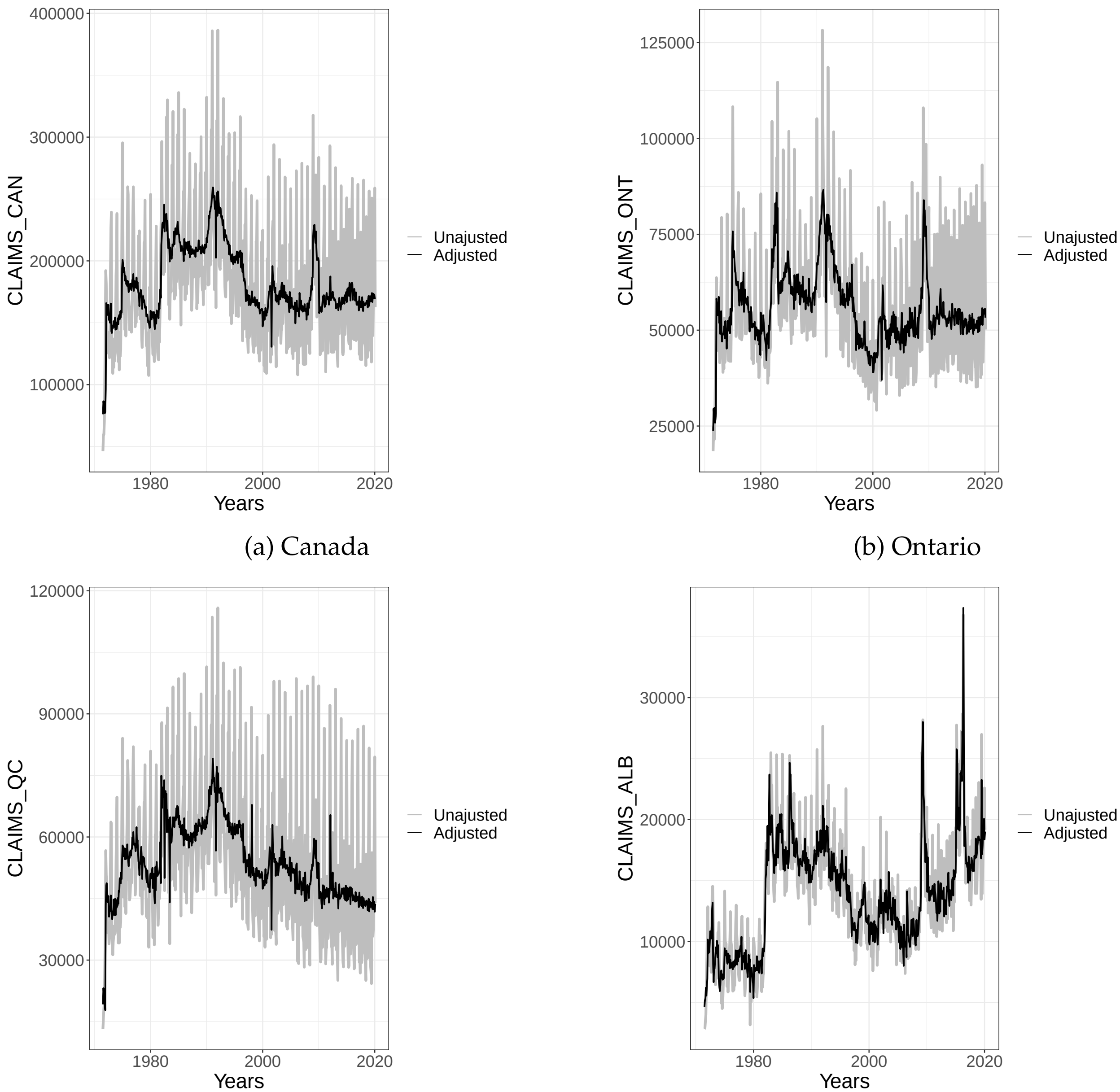
(d) Alberta

A.2 Factors' interpretation over time

Here, we study the factor interpretation through time by estimating the factor model recursively since 1990M12. The resulting time series form the basis of the heatmaps shown in Figures 13 and 14. For convenience, variables are grouped in categories, the exact composition of which are given in the data appendix. Tables 9 and 10 offer a more granular look in the interpretation and stability of factors, reporting the top ten series in terms of average squared loadings over subperiods. The subperiods have been chosen to match visual changes in some of the heatmaps, facilitating the parallel between the two.

The first factor weighs heavily and constantly on production variables. The factor appears

Figure 12: Seasonal adjustment of initial claims



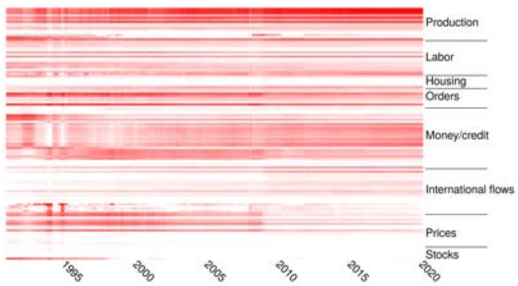
(a) Canada (b) Ontario

(c) Québec (d) Alberta

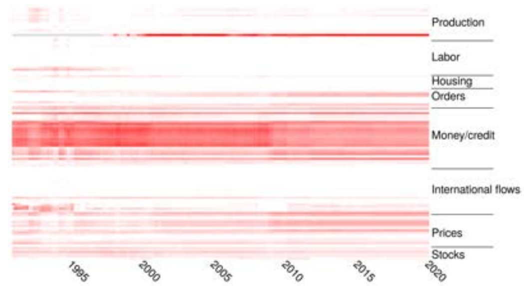
overall very stable and this can be confirmed by the ranking of series in three selected subperiods reproduced in Table 9. The second factor is clearly related to money and credit measures, even though few price and production series gain importance since 2010. The third factor used to be linked to international flows until 2003 but then turns to production and inflation series. The case of the fourth factor is interesting since it drastically changed since 2000, going from credit and house prices to exchange rates and stock returns.

Of course, further factors are harder to interpret given the natural ordering of importance of principal components. Nevertheless, there are some interesting patterns in factors 5 and 6. The former captures movements in orders until 2003, then is related to stock market and finally it

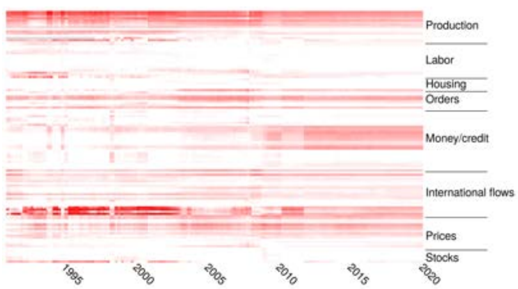
Figure 13: Heatmaps for factors 1 to 4



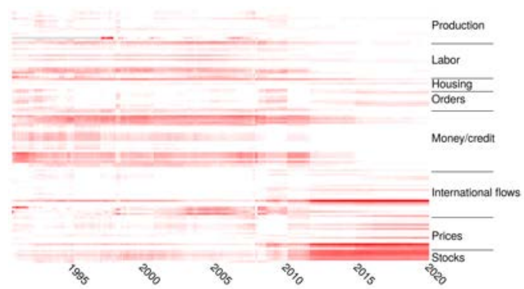
(a) Factor 1



(b) Factor 2



(c) Factor 3

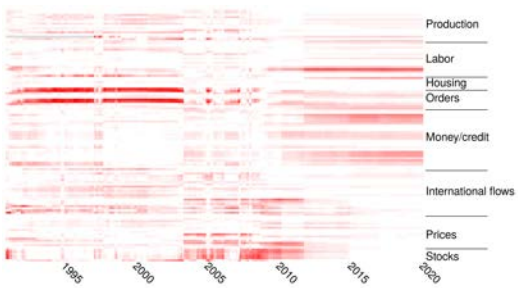


(d) Factor 4

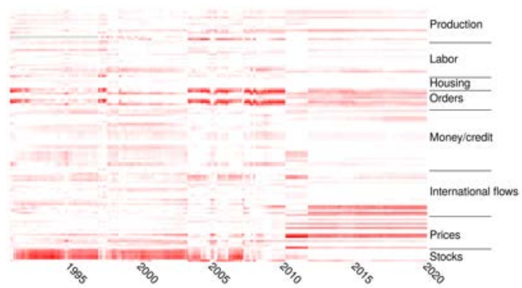
Note: Factors and loadings are estimated recursively using an expanding window. Displayed shades of red capture squared loadings.

mostly loads on labor market and money / credit. The latter has almost the opposite behaviour, but ends up being related to inflation and few international flows. The remaining factors are hard to interpret over time.

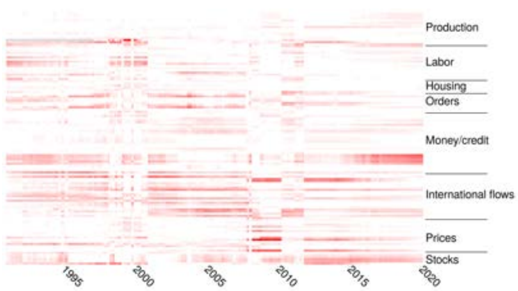
Figure 14: Heatmaps for factors 5 to 8



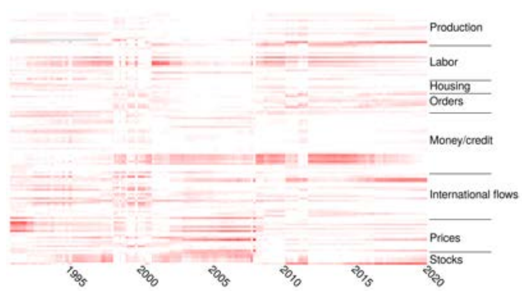
(a) Factor 5



(b) Factor 6



(c) Factor 7



(d) Factor 8

Note: Factors and loadings are estimated recursively using an expanding window. Displayed shades of red capture squared loadings.

Table 9: Top ten explained series for factors 1 to 4

Factor 1		
1991M1-2005M1	2005M1-2010M1	2010M1-2019M12
DUR_INV_RAT_new	BSI_new	BSI_new
MANU_INV_RAT_new	GDP_new	GDP_new
BSI_new	GPI_new	GPI_new
GPI_new	IP_new	IP_new
DM_new	DUR_INV_RAT_new	DM_new
GDP_new	DM_new	EMP_CAN
IP_new	MANU_INV_RAT_new	DUR_INV_RAT_new
EMP_CAN	EMP_CAN	MANU_INV_RAT_new
N_DUR_INV_RAT_new	N_DUR_INV_RAT_new	TBILL_3M
CPI_MINUS_FEN_CAN	CPI_MINUS_FEN_CAN	TBILL_6M
Factor 2		
1991M1-2005M1	2005M1-2010M1	2010M1-2019M12
TBILL_6M	GOV_AVG_1_3Y	G_AVG_10p.TBILL_3M
GOV_AVG_1_3Y	TBILL_6M	CRED_T
TBILL_3M	TBILL_3M	CRE_BUS
BANK_RATE_L	PC_PAPER_3M	G_AVG_5.10.Bank_rate
PC_PAPER_3M	GOV_AVG_3_5Y	TBILL_6M
GOV_AVG_3_5Y	BANK_RATE_L	GOV_AVG_1_3Y
MORTG_1Y	GOV_AVG_5_10Y	PC_PAPER_3M
MORTG_5Y	MORTG_5Y	TBILL_3M
GOV_AVG_5_10Y	MORTG_1Y	BANK_RATE_L
Factor 3		
1991M1-2005M1	2005M1-2010M1	2010M1-2019M12
CAN_SEC_NETFLOW	GDP_new	GDP_new
CAN_US_SEC_NETFLOW	GPI_new	BSI_new
GDP_new	BSI_new	CPI_MINUS_FOO_CAN
BSI_new	IP_new	GPI_new
CAN_EQTY_NETFLOW	CPI_MINUS_FOO_CAN	N_DUR_INV_RAT_new
GPI_new	N_DUR_INV_RAT_new	GOV_AVG_1_3Y
SPI_new	Exp_BP_new	CAN_US_SEC_NETFLOW
IP_new	MANU_INV_RAT_new	PC_PAPER_3M
CPI_MINUS_FOO_CAN	Imp_BP_new	TBILL_6M
N_DUR_INV_RAT_new	DUR_INV_RAT_new	TBILL_3M
Factor 4		
1991M1-2005M1	2005M1-2010M1	2010M1-2019M12
CRED_T	CRED_T	USDCAD_new
CRED_HOUS	CRED_HOUS	IPPI_MOTOR_CAN
NHOUSE_P_CAN	NHOUSE_P_CAN	TSX_LO
G_AVG_1.3.Bank_rate	CRED_CONS	TSX_CLO
UNEMP_DURAvg_CAN_new	EMP_CAN	TSX_HI
CRED_MORT	G_AVG_1.3.Bank_rate	IPPI_MACH_CAN
USDCAD_new	CAN_US_SEC_NETFLOW	SP500
G_AVG_3.5.Bank_rate	G_AVG_3.5.Bank_rate	DJ_CLO
CRED_CONS	G_AVG_5.10.Bank_rate	JPYCAD_new
EMP_CAN	CRED_MORT	WTISPLC

Note: Factor loadings estimated recursively with an expanding window. Rankings are based on mean squared loadings over the indicated period.

Table 10: Top ten explained series for factors 5 to 8

Factor 5		
1991M1-2005M1	2005M1-2010M1	2010M1-2019M12
DUR_N_ORD_new	SP500	UNEMP_DURAvg_CAN_new
MANU_UNFIL_new	DJ_CLO	CRED_T
DUR_UNFIL_new	TSX_LO	CRED_HOUS
MANU_N_ORD_new	USDCAD_new	G_AVG_1.3.Bank_rate
GOOD_HRS_CAN	TSX_CLO	G_AVG_3.5.Bank_rate
CAN_US_SEC_NETFLOW	TSX_HI	CLAIMS_CAN
CAN_EQTY_NETFLOW	IPPI_MOTOR_CAN	G_AVG_5.10.Bank_rate
WT_new	IPPI_CAN	NHOUSE_P_CAN
FOR_SEC_NETFLOW	CAN_SEC_NETFLOW	CRED_MORT
Imp_BP_new	CAN_US_SEC_NETFLOW	G_AVG_10p.TBILL_3M
Factor 6		
1991M1-2005M1	2005M1-2010M1	2010M1-2019M12
DJ_CLO	MANU_UNFIL_new	IPPI_ENER_CAN
SP500	DUR_UNFIL_new	IPPI_CAN
TSX_LO	DUR_N_ORD_new	CAN_US_SEC_NETFLOW
TSX_CLO	DUR_TOT_INV_new	CAN_EQTY_NETFLOW
TSX_HI	MANU_TOT_INV_new	CPI_GOO_CAN
MANU_UNFIL_new	OIL_ALB_new	CAN_SEC_NETFLOW
DUR_UNFIL_new	MANU_N_ORD_new	CPI_MINUS_FOO_CAN
DUR_N_ORD_new	OIL_CAN_new	CPI_ALL_CAN
MANU_TOT_INV_new	DJ_CLO	MANU_TOT_INV_new
IPPI_CAN	SP500	WTISPLC
Factor 7		
1991M1-2005M1	2005M1-2010M1	2010M1-2019M12
Exp_BP_new	IPPI_ENER_CAN	G_AVG_1.3.Bank_rate
Imp_BP_new	WTISPLC	DJ_CLO
DUR_TOT_INV_new	EX_TRANSP_BP_new	SP500
EX_TRANSP_BP_new	CAN_EQTY_NETFLOW	G_AVG_3.5.Bank_rate
MANU_TOT_INV_new	CAN_SEC_NETFLOW	IPPI_ENER_CAN
IMP_TRANSP_BP_new	CAN_US_SEC_NETFLOW	EOIL_BP_new
OIL_CAN_new	EX_ENER_BP_new	WTISPLC
OIL_ALB_new	EOIL_BP_new	TBILL_6M.Bank_rate
TBILL_6M.Bank_rate	IMP_TRANSP_BP_new	EX_ENER_BP_new
IPPI_METAL_CAN	Exp_BP_new	EX_TRANSP_BP_new
Factor 8		
1991M1-2005M1	2005M1-2010M1	2010M1-2019M12
UNEMP_DURA_1.4_CAN	IPPI_ENER_CAN	OIL_ALB_new
CPI_GOO_CAN	CPI_GOO_CAN	OIL_CAN_new
UNEMP_CAN	G_AVG_1.3.Bank_rate	G_AVG_1.3.Bank_rate
CPI_ALL_CAN	CPI_ALL_CAN	EOIL_BP_new
IPPI_CAN	G_AVG_3.5.Bank_rate	EMP_MANU_CAN
EX_TRANSP_BP_new	G_AVG_5.10.Bank_rate	EX_ENER_BP_new
EMP_MANU_CAN	CPI_MINUS_FOO_CAN	TBILL_6M.Bank_rate
USDCAD_new	WTISPLC	G_AVG_3.5.Bank_rate
SP500	TBILL_6M.Bank_rate	UNEMP_CAN
TSX_CLO	G_AVG_10p.TBILL_3M	G_AVG_5.10.Bank_rate

Note: Factor loadings estimated recursively with an expanding window. Rankings are based on mean squared loadings over the indicated period.

A.3 Forecasting results: rolling window

Table 11: Forecasting real activity

	Industrial Production				Employment				Unemployment			
Models	h=1	h=3	h=6	h=12	h=1	h=3	h=6	h=12	h=1	h=3	h=6	h=12
AR,BIC (RMSE)	0.010	0.006	0.005	0.004	0.002	0.001	0.001	0.001	0.186	0.111	0.093	0.083
ARDI,BIC	0.96**	0.90***	0.97	0.91**	0.97	0.98	1.00	1.00	0.96**	0.88**	0.85***	0.91**
Elastic-Net-X	0.95**	0.91***	0.96	1.03	1.00	1.08*	1.11**	1.22***	1.02	0.94	0.96	1.15***
Ridge-X	0.95***	0.93***	0.92***	0.95	1.02	1.04	1.05	1.02	0.97*	0.90***	0.89***	0.97
Lasso-X	0.94***	0.92***	0.94**	1.00	0.99	1.02	1.06*	1.23***	0.99	0.96	0.98	1.12**
Adaptive-Lasso-X	0.95***	0.92***	0.93**	1.00	0.99	1.01	1.07*	1.21***	1.00	0.95	0.95	1.10**
RF-X	0.95***	0.95**	0.99	0.92**	0.99	1.00	1.03	1.04	0.95***	0.93**	0.98	1.04
ARDI,Elastic-Net	0.96**	0.93***	0.95*	1.11	0.99	1.04	1.00	1.06	1.00	0.90**	0.92*	0.98
ARDI,Ridge	0.97***	0.97*	0.97**	1.08	1.05	1.10*	1.02	1.09	0.98*	0.91***	0.89***	0.92*
ARDI,Lasso	0.96***	0.93***	0.93**	0.89**	0.98	1.00	1.04	1.04	0.99	0.92**	0.91**	1.06
ARDI,Adaptive-Lasso	0.96**	0.95**	0.93**	0.89**	0.98*	0.99	1.01	1.01	0.99	0.90**	0.90***	1.10
RFARDI	0.96***	0.94***	0.94***	0.92***	0.99	1.04	1.04	1.04	0.97**	0.93*	0.92***	0.97
T-CSR5	0.95***	0.92***	0.96	0.92**	0.97*	0.95*	0.96*	1.00	0.97*	0.92**	0.90***	0.96
T-CSR10	0.95***	0.92***	0.99	1.00	0.99	0.96	0.96	1.02	0.97	0.92**	0.89***	1.01
T-CSR20	0.97	0.96	1.07	1.16**	1.04*	1.01	1.01	1.09	1.00	0.98	0.93	1.15*

Note: See table 3.

Table 12: Forecasting inflation

	CPI				Core CPI			
Models	h=1	h=3	h=6	h=12	h=1	h=3	h=6	h=12
AR,BIC (RMSE)	0.004	0.002	0.002	0.001	0.003	0.002	0.001	0.001
ARDI,BIC	0.99	0.99	1.04	0.83**	0.99	0.97	0.98	0.90
Elastic-Net-X	0.96***	0.94***	1.04	1.04	0.93***	0.94**	1.09*	1.03
Ridge-X	0.98**	0.97***	0.99	0.82**	0.97	1.01	0.97	0.94
Lasso-X	0.96***	0.95***	1.03	0.93	0.94***	0.96	1.10**	0.99
Adaptive-Lasso-X	0.96***	0.94***	1.02	0.95	0.94***	0.97*	1.10**	0.97
RF-X	0.95***	0.95***	0.98	0.87***	0.93***	0.94**	1.00	0.87**
ARDI,Elastic-Net	0.98*	0.99	1.13*	0.98	0.95***	0.94**	0.96	1.01
ARDI,Ridge	0.99	0.98***	1.03	0.98	0.99	1.04**	1.07***	0.97**
ARDI,Lasso	1.00	0.97*	1.09*	0.84**	0.96***	0.99	1.00	0.93
ARDI,Adaptive-Lasso	0.99	0.98*	1.12*	0.86**	0.96**	0.99	0.99	0.93
RFARDI	0.98**	0.94***	0.95	0.90***	0.95***	0.96	0.91*	0.91**
T-CSR5	0.97*	0.97	1.01	0.90**	0.95***	0.95*	1.03	0.97
T-CSR10	0.99	1.01	1.06	0.88**	0.97**	0.97	1.09*	1.02
T-CSR20	1.02	1.05	1.19***	0.92	1.01	1.01	1.17**	1.12

Note: See table 3.

Table 13: Forecasting credit markets

	Total Credit				Business Credit				Consumption Credit			
Models	h=1	h=3	h=6	h=12	h=1	h=3	h=6	h=12	h=1	h=3	h=6	h=12
AR,BIC (RMSE)	0.002	0.001	0.001	0.002	0.003	0.002	0.002	0.002	0.003	0.002	0.002	0.003
ARDI,BIC	1.04**	1.04*	1.03	0.97	1.00	1.03	0.99	1.00	1.04**	1.04*	1.02	1.04
Elastic-Net-X	1.01	0.99	1.18***	1.24***	0.98	0.95*	1.04	1.12*	1.06**	1.10**	1.10*	1.15***
Ridge-X	1.08**	1.09*	1.27***	1.30***	1.01	1.05	1.13**	1.07	1.12***	1.13***	1.14***	1.13***
Lasso-X	1.02	0.98	1.16***	1.22***	1.01	0.92**	1.01	1.12*	1.09**	1.09**	1.10*	1.16***
Adaptive-Lasso-X	1.04	1.01	1.16***	1.23***	1.00	0.95*	1.04	1.13*	1.09**	1.11**	1.10*	1.15***
RF-X	1.00	1.09*	1.22**	1.28***	1.00	1.06*	1.18***	1.18**	1.02	1.08*	1.16**	1.23***
ARDI,Elastic-Net	1.03*	1.01	1.07**	1.19**	1.00	0.98	0.94*	1.13	1.08***	1.03	1.02	1.10
ARDI,Ridge	1.28***	1.15***	1.31***	1.26***	1.10***	1.18**	1.11**	1.02	1.24***	1.34***	1.24***	1.15***
ARDI,Lasso	1.04*	0.98	1.02	1.20***	1.00	0.93*	0.93**	1.03	1.07***	1.09**	1.00	1.03
ARDI,Adaptive-Lasso	1.02	0.99	1.03	1.23***	1.00	0.93*	0.93*	1.10*	1.08***	1.03	1.02	1.05
RFARDI	1.01	1.06*	1.18***	1.15***	0.98	1.01	1.12***	1.09**	1.02	1.04	1.05	1.08**
T-CSR5	1.00	0.95**	0.96*	1.10**	0.98*	0.93***	0.90***	0.95*	0.97	0.96**	0.96*	1.00
T-CSR10	1.04**	0.99	1.00	1.22***	1.02	0.96*	0.90***	1.01	1.01	0.99	0.98	1.03
T-CSR20	1.13***	1.10**	1.13**	1.39***	1.08***	1.01	0.95*	1.15**	1.07**	1.10**	1.06	1.07

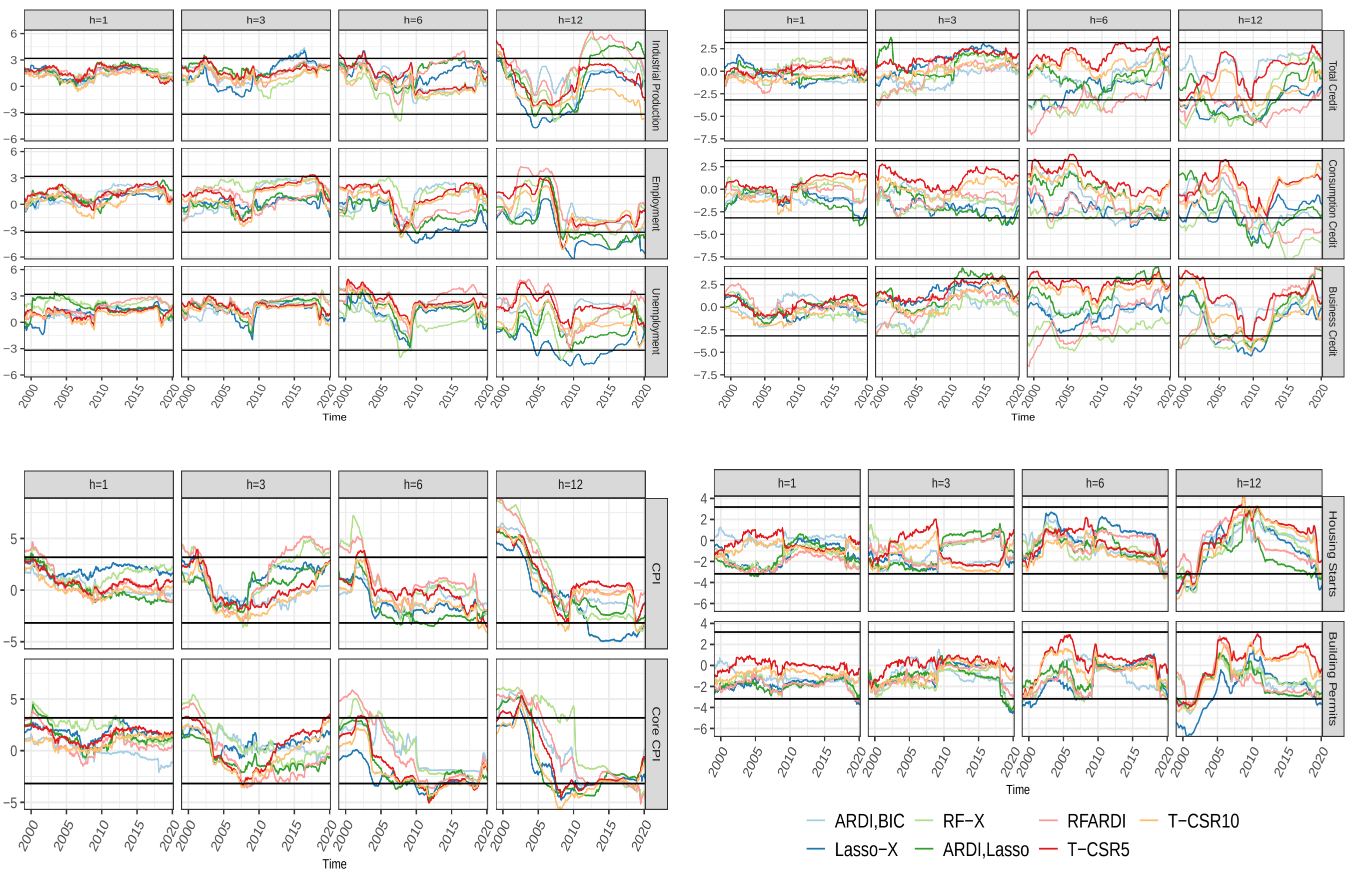
Note: See table 3.

Table 14: Forecasting the housing market

	Housing starts				Building Permits			
Models	h=1	h=3	h=6	h=12	h=1	h=3	h=6	h=12
AR,BIC (RMSE)	0.090	0.041	0.027	0.018	0.078	0.033	0.021	0.014
ARDI,BIC	1.00	1.05*	1.03	1.06	1.02**	1.03*	1.03***	1.06**
Elastic-Net-X	1.11***	1.03*	1.06**	1.23***	1.14***	1.06*	1.09***	1.22***
Ridge-X	1.07***	1.02	1.01	1.18***	1.10***	1.05**	1.07**	1.12***
Lasso-X	1.05**	1.04*	1.01	1.18**	1.07***	1.04	1.07**	1.26***
Adaptive-Lasso-X	1.05***	1.02	1.02	1.08**	1.08***	1.04*	1.04*	1.14**
RF-X	1.06***	1.02	1.04**	1.06**	1.07***	1.04*	1.07**	1.04
ARDI,Elastic-Net	1.05***	1.03	1.05***	1.09**	1.08***	1.03	1.11**	1.22**
ARDI,Ridge	1.07***	1.02	1.00	1.05**	1.10***	1.04*	1.06**	1.04
ARDI,Lasso	1.04***	1.02	1.04*	1.10***	1.06***	1.04**	1.05*	1.19**
ARDI,Adaptive-Lasso	1.03**	1.01	1.03**	1.13***	1.06***	1.03*	1.08**	1.20**
RFARDI	1.07***	1.03	1.02	1.04**	1.07***	1.04*	1.07**	1.04
T-CSR5	1.02	1.06	1.04	1.08*	1.02	1.03	1.03	1.06*
T-CSR10	1.05**	1.10**	1.08**	1.17**	1.05***	1.06**	1.08**	1.15**
T-CSR20	1.08***	1.20***	1.25***	1.40**	1.12***	1.13***	1.18***	1.40**

Note: See table 3.

Figure 15: Forecasting performance over time: fluctuation test



Note: The figure shows the Giacomini-Rossi fluctuation test for best RMSPE models against the ARD benchmark. Solide lines correspond to 10% critical value.

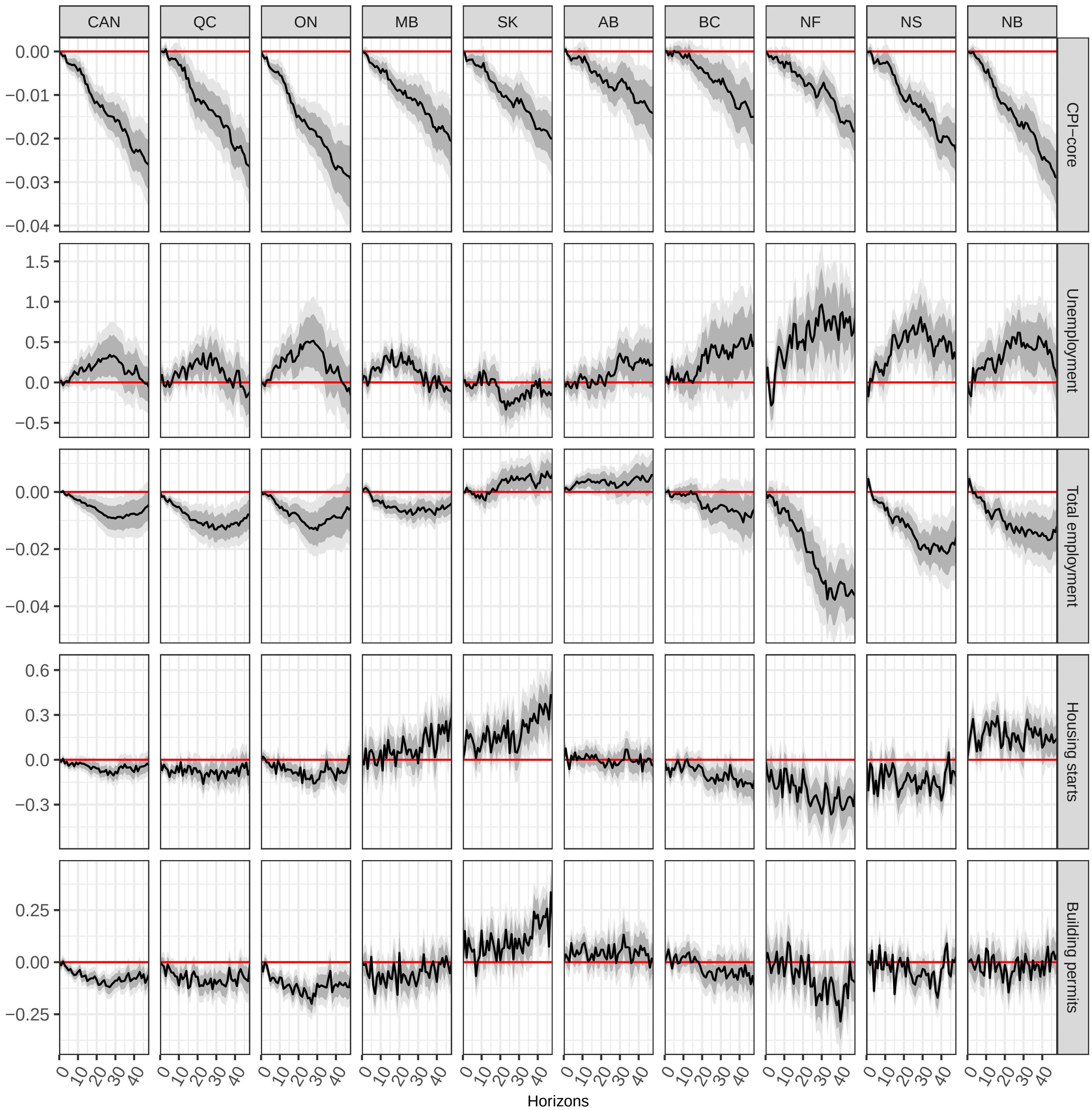
A.4 Impulse response functions

Figure 16 show the main results for the aggregate series when considering observations from 1981M01 to 2015M10. When looking at inflation and unemployment one pattern emerge, monetary shocks have larger effects in central Canada (Québec and Ontario) than in the prairies, British-Columbia and New Foundland. The effect on inflation is slowly decaying as one move west and the shape of the IRFs for unemployment follow a hump shape in Québec and Ontario while it's less clear in the other provinces. Unemployment in Alberta and British Columbia eventually rises but the effect in Manitoba and Saskatchewan are quite small and counterintuitive with reductions in unemployment after around two years. We can also see a similar pattern for total employment but in this case Manitoba joins Québec and Ontario with decreases in employment following a monetary policy shock. Atlantic provinces are affected the most by the shock. In Québec and Ontario housing starts drops while it takes more time in Alberta and British-Columbia and we see the opposite in Manitoba and Saskatchewan with an increase in housing starts. As for housing prices, they clearly decrease in Ontario, Alberta and British-Columbia but increases in Québec before starting to decrease after 30 months. Manitoba and Saskatchewan have again their own specific patterns with increases in housing prices.

Figure 17 reports same IRFs but estimated since inflation targeting. Using only the inflation targeting (IT) period we find similar results to those of Champagne and Sekkel (2018) when looking specifically at Canada. Figure 18 shows that monetary policy shocks in Canada have smaller effects in the IT period than in the entire period. While prices dropped by 2% in the full sample they only drop by around 0.7 % in the post-1992 estimation.[19] The differences for unemployment are even more important as the shocks no longer have a significant effect using in the IT period. This suggests that monetary policy have become more effective since inflation targeting (Boivin and Giannoni, 2006). We find similar results for the provinces but again there are important differences. Monetary policy continued to have significant effects on prices in Québec and Ontario but not in the other provinces. The effect on unemployment is interesting as Ontario's unemployment rate is no longer affected by monetary policy shocks but Québec's and Manitoba's are.

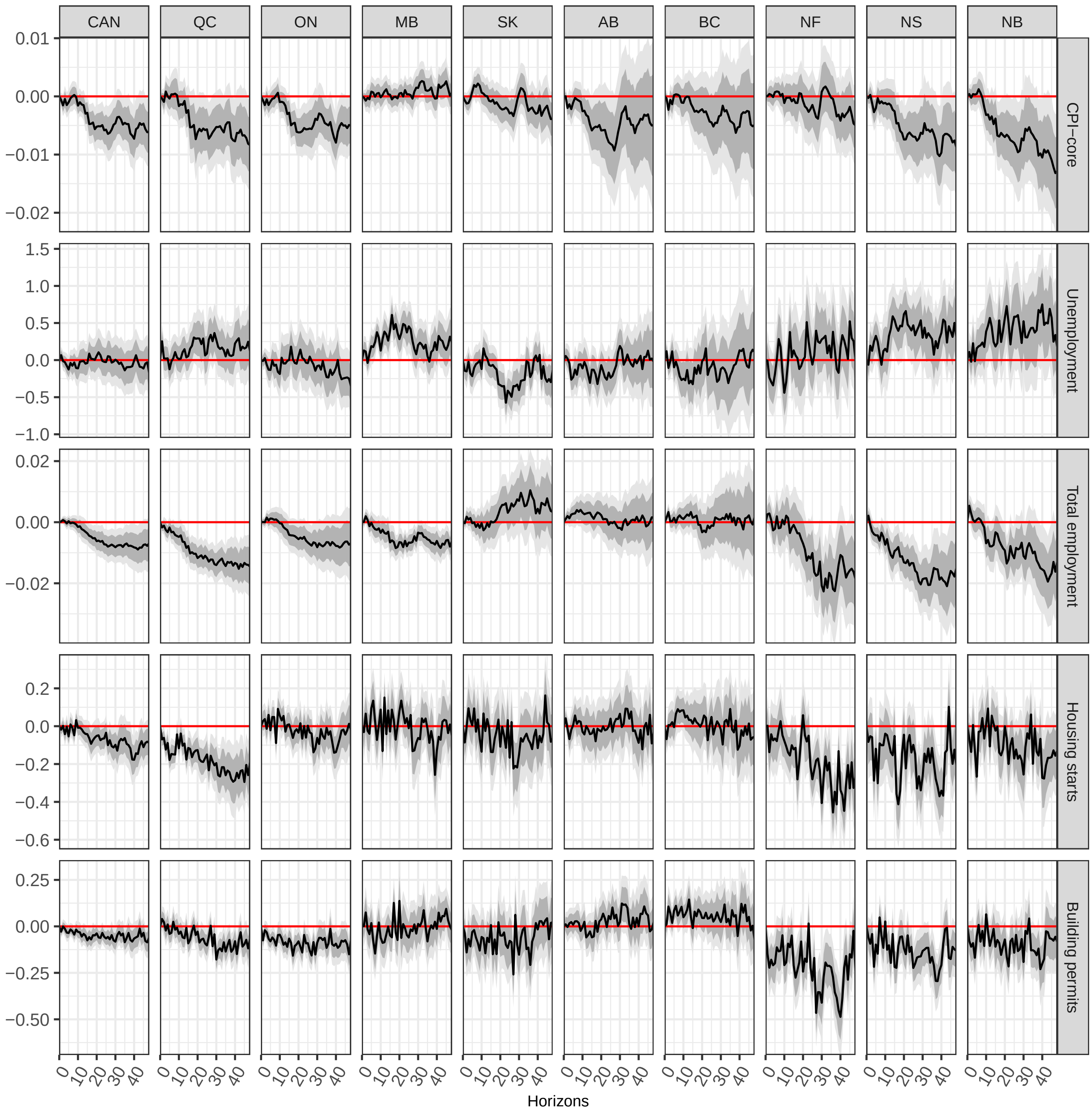
[19]We also find smaller effects of monetary policy shocks in the post-1992 period for price components.

Figure 16: Impulse response functions of aggregate series - 1981m1-2015m10



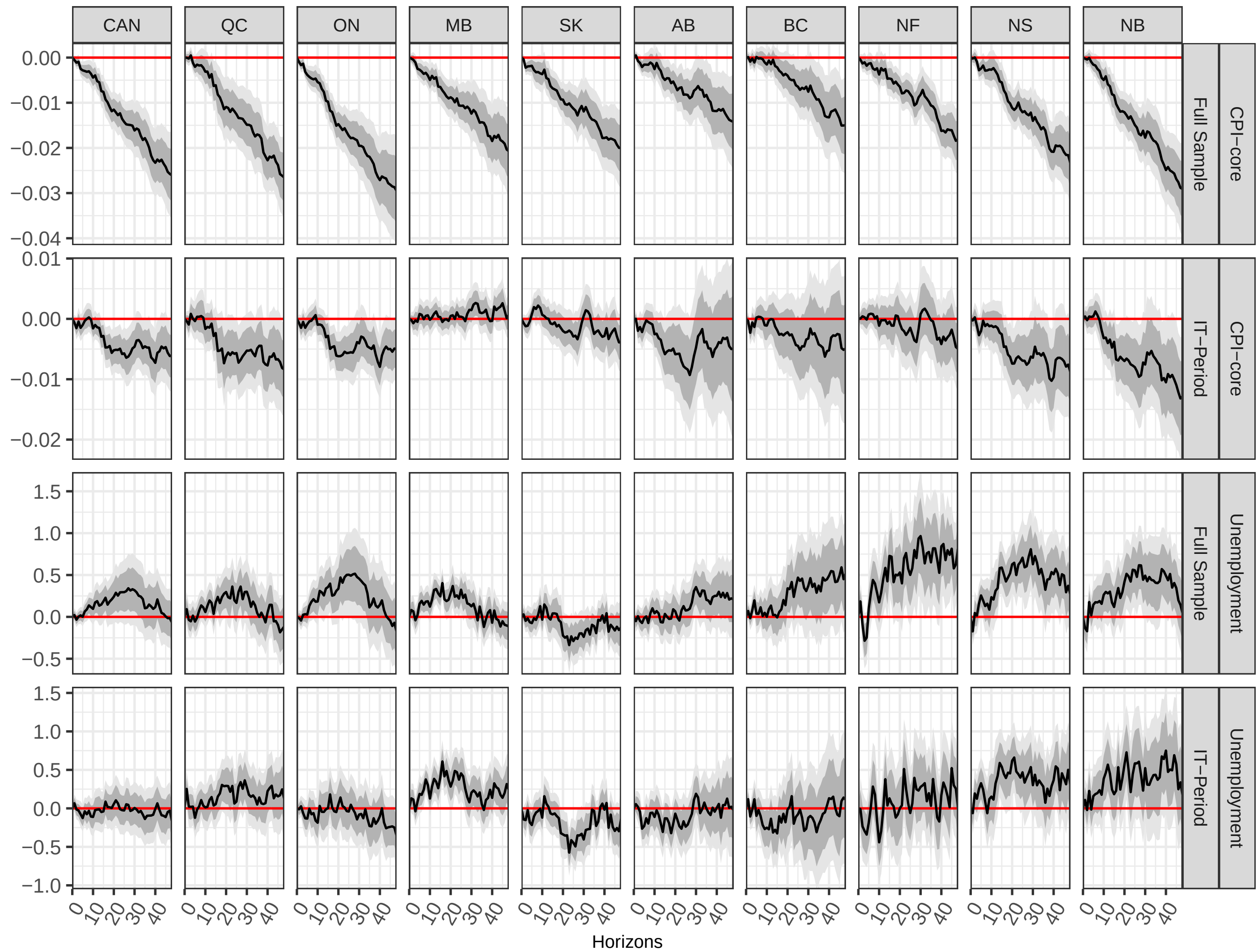
Note: Dark and light gray shades are 68% and 90% confidence bands constructed using HAC standard errors.

Figure 17: Impulse response functions of aggregate series - 1992m1-2015m10



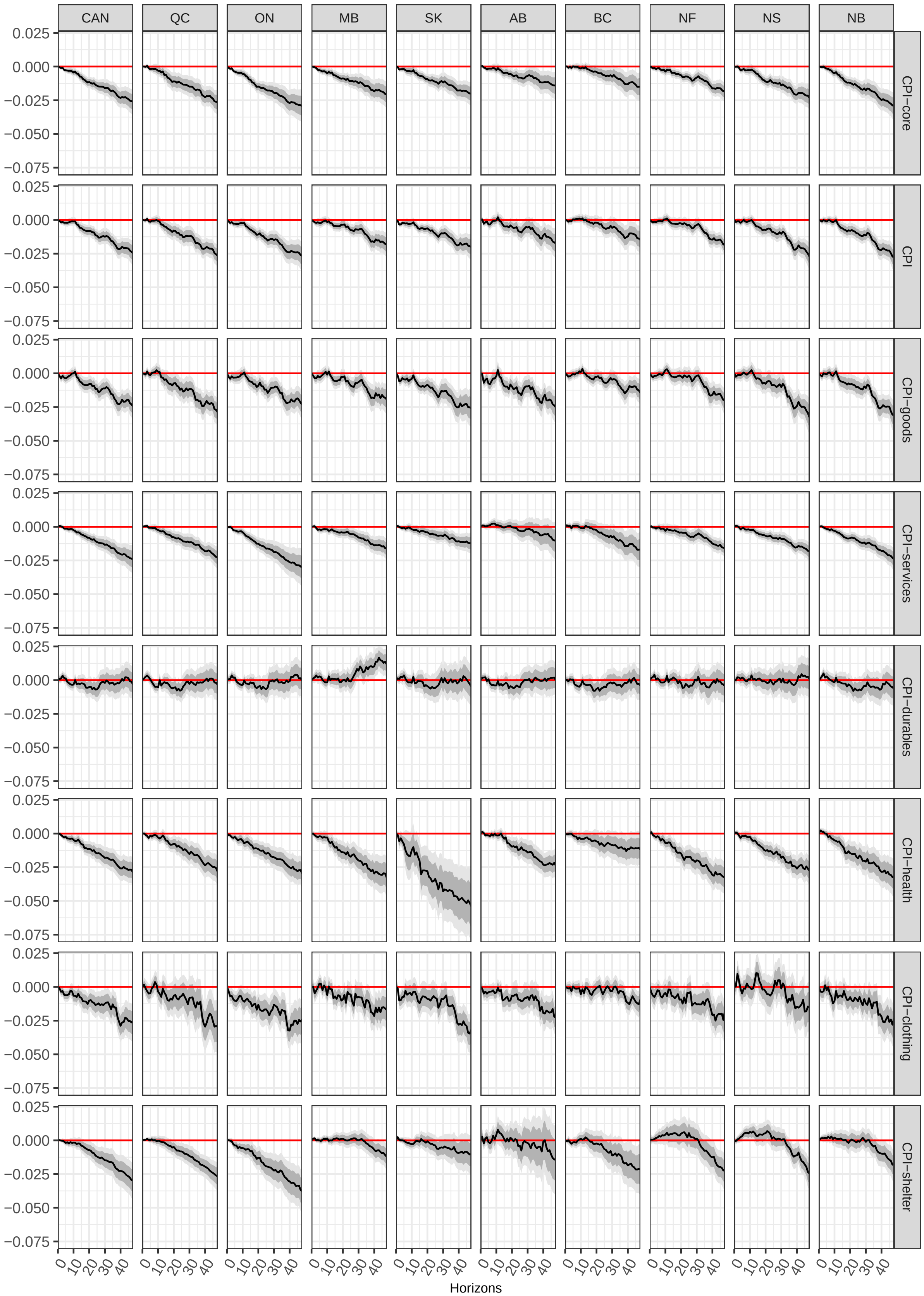
Note: Dark and light gray shades are 68% and 90% confidence bands constructed using HAC standard errors.

Figure 18: Comparison of IRFs: full sample versus IT period



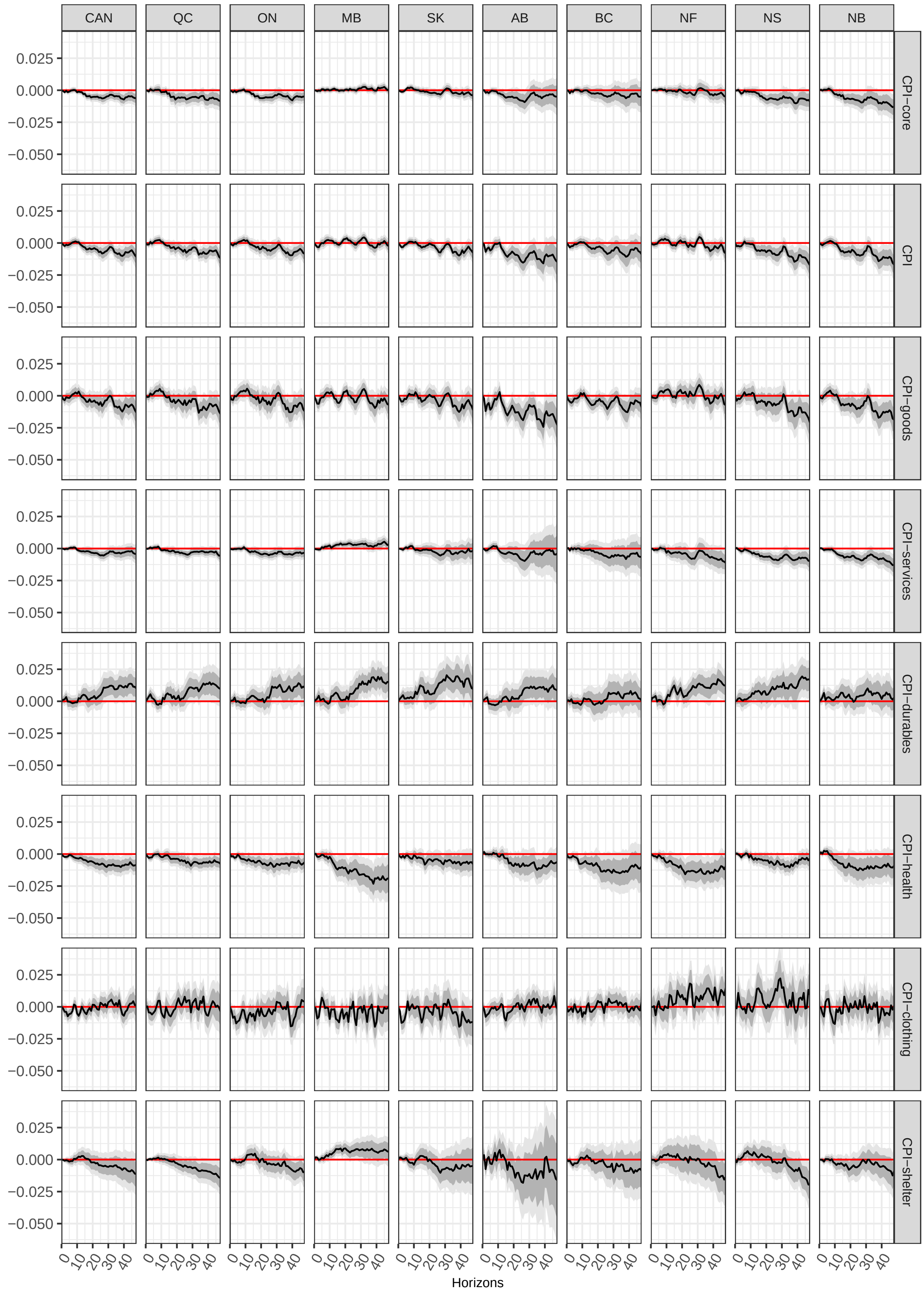
Note: Dark and light gray shades are 68% and 90% confidence bands constructed using HAC standard errors.

Figure 19: Comparison of IRFs: CPI - full sample



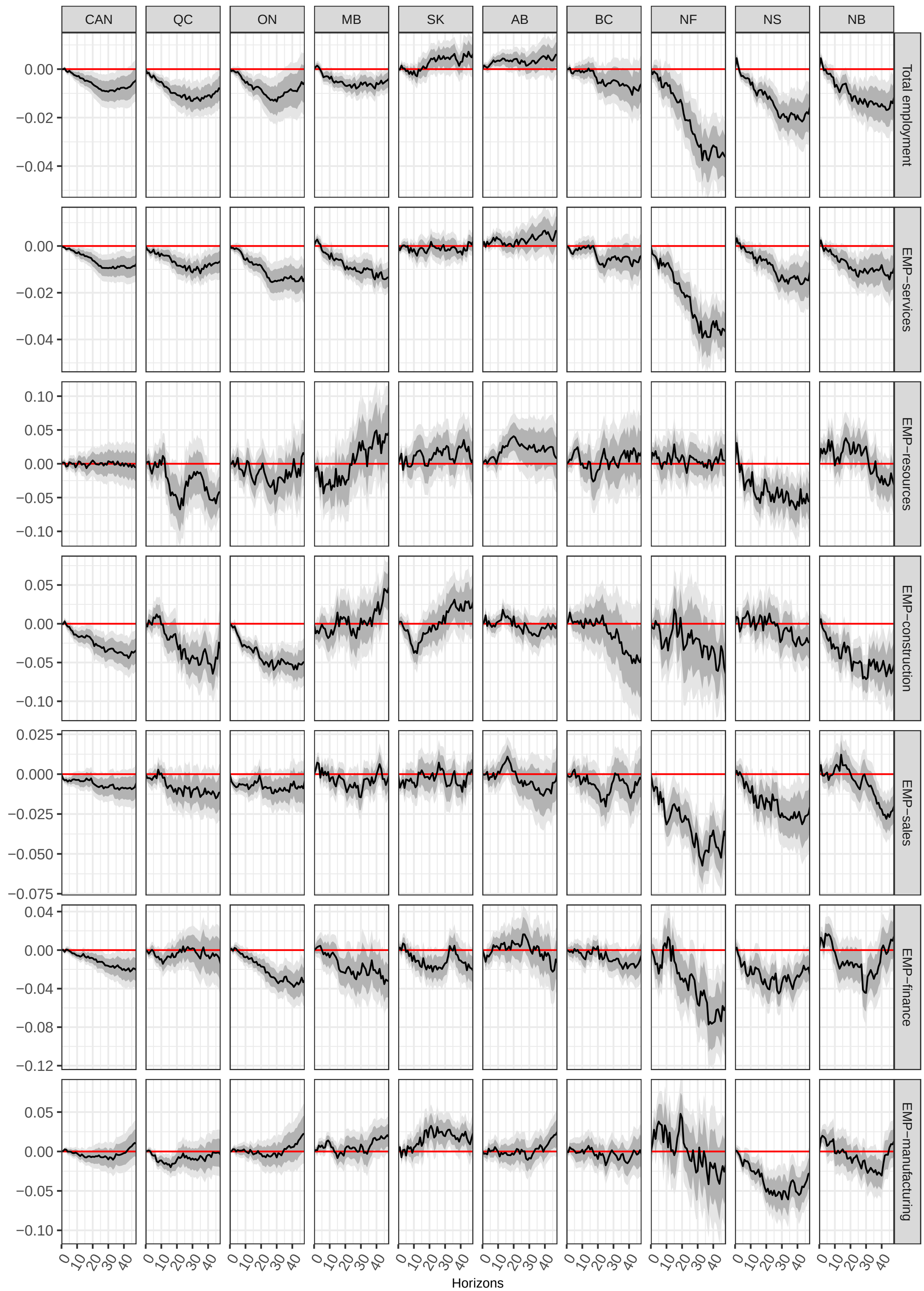
Note: Dark and light gray shades are 68% and 90% confidence bands constructed using HAC standard errors.

Figure 20: Comparison of IRFs: CPI - IT period



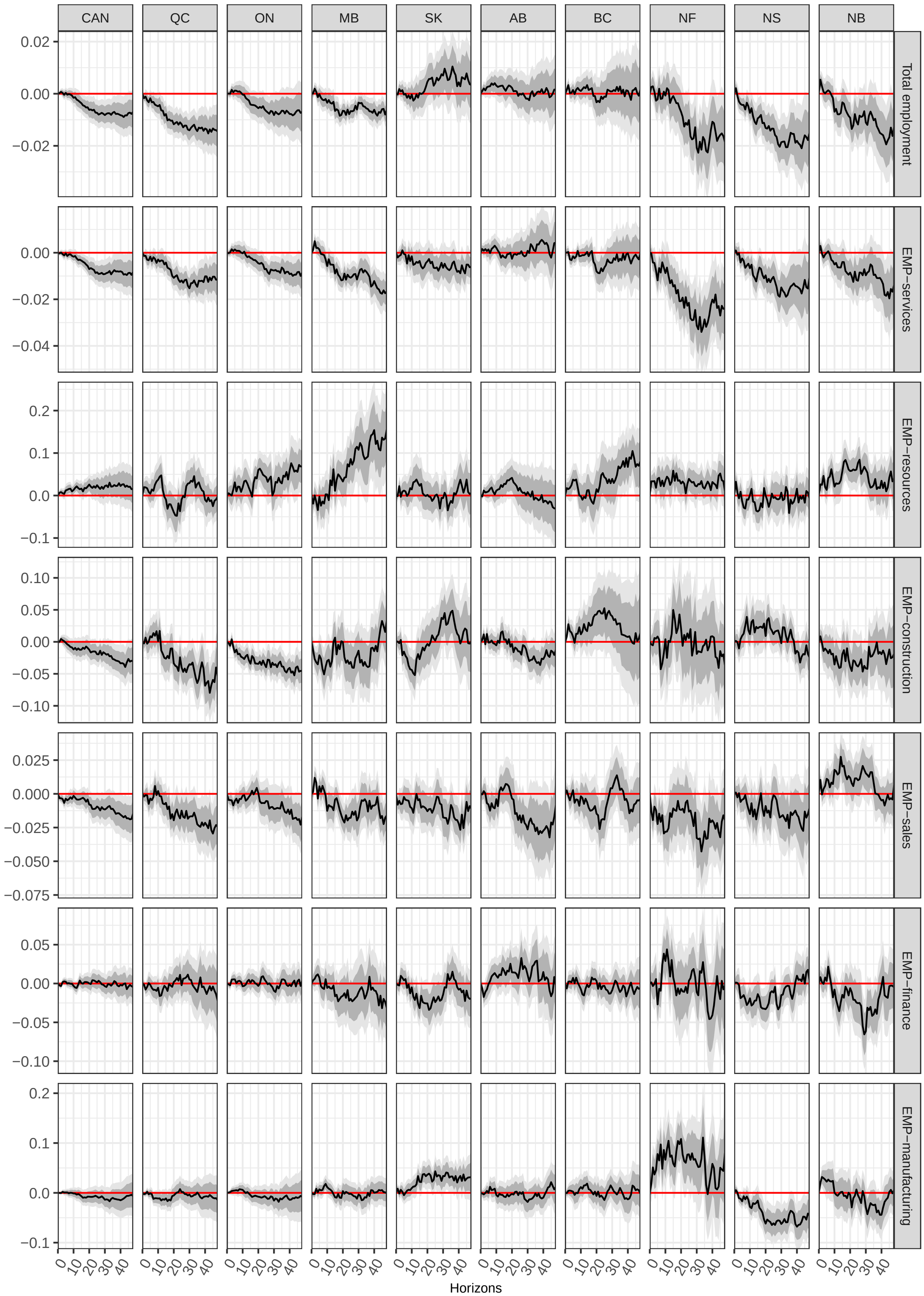
Note: Dark and light gray shades are 68% and 90% confidence bands constructed using HAC standard errors.

Figure 21: Comparison of IRFs: EMP - full sample



Note: Dark and light gray shades are 68% and 90% confidence bands constructed using HAC standard errors.

Figure 22: Comparison of IRFs: EMP - IT period



Note: Dark and light gray shades are 68% and 90% confidence bands constructed using HAC standard errors.

B ONLINE APPENDIX - Data Sets

The transformation codes are: 1 - no transformation; 2 - first difference; 4 - logarithm; 5 - first difference of logarithm. Vector(1) and Vector(2) indicate StatCan vectors. When different series are needed to construct an indicator of interest because of the break indicated by column Date, Vector(1) is the most recent series. Some variables are taken from the Federal Reserve of St-Louis Economic Data Base (FRED), from the Bank of Canada (BoC) and Yahoo Finance.

No	Variable	Description	Region	Vector(1)	Vector(2)	Date	T-code
		PRODUCTION					
1	GDP_new	GDP total	CAN	v41881478	v65201483	1997M1	5
2	BSI_new	GDP business	CAN	v41881479	v65201486	2007M1	5
3	GPI_new	GDP goods	CAN	v41881485	v65201484	1997M1	5
4	SPI_new	GDP services	CAN	v41881486	v65201485	1997M1	5
5	IP_new	GDP industrial production	CAN	v41881487	v65201492	1997M1	5
6	NDM_new	GDP non durable goods	CAN	v41881488	v65201493	1997M1	5
7	DM_new	GDP durables	CAN	v41881489	v65201494	1997M1	5
8	OILP_new	GDP mining, petrol and gas	CAN	v41881501	v65201509	1997M1	5
9	CON_new	GDP construction	CAN	v41881523	v65201531	1997M1	5
10	RT_new	GDP retail trade	CAN	v41881688	v65201641	1997M1	5
11	WT_new	GDP wholesale trade	CAN	v41881689	v65201631	1997M1	5
12	PA_new	GDP public administration	CAN	v41881775	v65201749	1997M1	5
13	FIN_new	GDP finance and insurance	CAN	v41881725	v65201680	1997M1	5
14	OIL_CAN_new	Crude oil production (Cubic meters)	CAN	v17948	v107757044	2016M1	5
15	OIL_ALB_new	Crude oil production (ALB) (Cubic meters)	ALB	v18050	v107757710	2016M1	5
		LABOR MARKET					
16	EMP_CAN	Employment total	CAN	v24793			5
17	EMP_SERV_CAN	Employment services	CAN	v2057610			5
18	EMP_FOR_OIL_CAN	Employment forestry, fishing, mining, oil and gas	CAN	v2057606			5
19	EMP_CONS_CAN	Employment construction	CAN	v2057608			5
20	EMP_SALES_CAN	Employment sales (wholesale and retail trade)	CAN	v2057611			5
21	EMP_FIN_CAN	Employment finance, insurance and real estate	CAN	v2057613			5
22	EMP_MANU_CAN	Employment manufacturing	CAN	v2057609			5
23	EMP_PART_CAN	Employment part time	CAN	v2062813			5
24	UNEMP_CAN	Unemployment rate LRUNTTTTCAM156S	CAN	(FRED)	v2062815	1976M1	2
25	UNEMP_DURA_1-4_CAN	Unemployment duration (1-4 weeks)	CAN	v1078667742			5
26	UNEMP_DURA_5-13_CAN	Unemployment duration (5-13 weeks)	CAN	v1078667850			5
27	UNEMP_DURA_14-25_CAN	Unemployment duration (14-24 weeks)	CAN	v1078667958			5
28	UNEMP_DURA_27+_CAN	Unemployment duration (27+ weeks)	CAN	v1078668066			5
29	UNEMP_DURAvg_CAN_new	Unemployment average duration	CAN	v3433887	v1078668391	1997M1	5
30	CLAIMS_CAN	Employment insurance initial claims, Allowed	CAN	v383942			1
31	TOT_HRS_CAN	Hours worked total	CAN	v4391505			5
32	GOOD_HRS_CAN	Hours worked goods	CAN	v4391507			5
		HOUSING AND CONSTRUCTION					
33	NHOUSE_P_CAN	New housing price index, Total (house and land)	CAN	v111955442			5
34	hstart_CAN_new	Housing starts (units)	CAN	v730413	v52300157	1990M1	5
35	build_Total_CAN_new	Building permits (tous)	CAN	v42061	v121293395	2011M1	5
36	build_Ind_CAN_new	Building permits (industries)	CAN	v42064	v121301795	2011M1	5
37	build_Comm_CAN_new	Building permits (commerce)	CAN	v42065	v121304915	2011M1	5
		MANUFACTURING, SALES AND INVENTORIES					
38	MANU_N_ORD_new	Manufacturing new orders (total)	CAN	v723019	v800913	1992M1	5
39	MANU_UNFIL_new	Manufacturing unfilled orders (total)	CAN	v723313	v803189	1992M1	5
40	MANU_TOT_INV_new	Manufacturing inventories (total)	CAN	v724933	v803227	1992M1	5
41	MANU_INV_RAT_new	Manufacturing inventories to shipments ratio (total)	CAN	v725059	v803313	1992M1	1
42	N_DUR_INV_RAT_new	Manufacturing inventories to shipments ratio (durables)	CAN	v725060	v803314	1992M1	1
43	DUR_N_ORD_new	Manufacturing new orders (durables)	CAN	v723034	v800926	1992M1	5
44	DUR_UNFIL_new	Manufacturing unfilled orders (durables)	CAN	v723328	v803202	1992M1	5
45	DUR_TOT_INV_new	Manufacturing inventories (durables)	CAN	v724948	v803240	1992M1	5
46	DUR_INV_RAT_new	Manufacturing inventories to shipments ratio (durables)	CAN	v725074	v803326	1992M1	1
		MONEY AND CREDIT					
47	M3	M3 (gross)	CAN	v41552794			5
48	M2p	M2+ (gross)	CAN	v41552798			5
49	M_BASE1	Monetary base	CAN	v37145			5
50	CRED_T	Total credit	CAN	v36414			5
51	CRED_HOUS	Household credit	CAN	v36415			5
52	CRED_MORT	Mortgage credit	CAN	v36416			5
53	CRED_CONS	Consumption credit	CAN	v36417			5
54	CRE_BUS	Business credit	CAN	v36418			5
55	BANK_RATE_L	Bank rate	CAN	v122550			2
56	PC_PAPER_1M	Corporate paper rate (1 month)	CAN	v122509	IIROC	2019M1	2
57	PC_PAPER_3M	Corporate paper rate (3 months)	CAN	v122491	IIROC	2019M1	2
58	GOV_AVG_1_3Y	Governmental bonds (average rate) (1-3 years)	CAN	v122558			2
59	GOV_AVG_3_5Y	Governmental bonds (average rate) (3-5 years)	CAN	v122485			2
60	GOV_AVG_5_10Y	Governmental bonds (average rate) (5-10 years)	CAN	v122486			2
61	GOV_AVG_10pY	Governmental bonds (average rate) (10+ years)	CAN	v122487			2
62	MORTG_1Y	Mortgage rate (1 year) BoC	CAN	v122520	(V80691333)	2019M10	2
63	MORTG_5Y	Mortgage rate (5 years) BoC	CAN	v122521	(V80691335)	2019M10	2
64	TBILL_3M	Treasury bills (3 months)	CAN	v122541			2
65	TBILL_6M	Treasury bills (6 months)	CAN	v122552			2
66	PC_3M-Bank_rate	Corporate paper rate (3 months) - Bank rate	CAN	Difference			1
67	G_AVG_1-3-Bank_rate	Government bonds (1-3 years) - Bank rate	CAN	Difference			1
68	G_AVG_3-5-Bank_rate	Government bonds (3-5 years) - Bank rate	CAN	Difference			1
69	G_AVG_5-10-Bank_rate	Government bonds (5-10 years) - Bank rate	CAN	Difference			1
70	TBILL_6M-Bank_rate	Treasury bond (6 months) - Bank rate	CAN	Difference			1
71	G_AVG_10p-TBILL_3M	Government Bonds (10+ years) - TBILL_3M	CAN	Difference			1
		INTERNATIONAL TRADE AND FLOWS					
72	RES_TOT	Total Canada's official international reserves	CAN	v122396			5
73	RES_USD	Canadian USD reserves	CAN	v122398			5
74	RES_IMF	Canadian reserve position at the IMF	CAN	v122401			5

No	Variable	Description	Region	Vector(1)	Vector(2)	Date	T-code
75	Imp_BP_new	Imports total	CAN	v183406	v1001826653	1988M1	5
76	IOIL_BP_new	Imports oil	CAN	v183426	v1001826667	1988M1	5
77	Exp_BP_new	Exports total	CAN	v191490	v1001827265	1988M1	5
78	EOIL_BP_new	Exports oil	CAN	v191516	v1001827279	1988M1	5
79	EX_ENER_BP_new	Export energy products	CAN	v191516	v1001827278	1988M1	5
	(Sum)	Export energy products	CAN	v191517	v1001827278	1988M1	
	(Sum)	Export energy products	CAN	v191504	v1001827278	1988M1	
	(Sum)	Export energy products	CAN	v191533	v1001827278	1988M1	
80	EX_MINER_BP_new	Exports non-metallic ores	CAN	v191511	v1001827292	1988M1	5
	(Sum)	Exports non-metallic ores	CAN	v191512	v1001827292	1988M1	
	(Sum)	Exports non-metallic ores	CAN	v191513	v1001827292	1988M1	
	(Sum)	Exports non-metallic ores	CAN	v191514	v1001827292	1988M1	
	(Sum)	Exports non-metallic ores	CAN	v191515	v1001827292	1988M1	
	(Sum)	Exports non-metallic ores	CAN	v191508	v1001827292	1988M1	
81	EX_METAL_BP_new	Exports metal and other mineral products	CAN	v191522	v1001827303	1988M1	5
	(Sum)	Exports metal and other mineral products	CAN	v191523	v1001827303	1988M1	
	(Sum)	Exports metal and other mineral products	CAN	v191524	v1001827303	1988M1	
	(Sum)	Exports metal and other mineral products	CAN	v191525	v1001827303	1988M1	
	(Sum)	Exports metal and other mineral products	CAN	v191526	v1001827303	1988M1	
	(Sum)	Exports metal and other mineral products	CAN	v191527	v1001827303	1988M1	
	(Sum)	Exports metal and other mineral products	CAN	v191528	v1001827303	1988M1	
	(Sum)	Exports metal and other mineral products	CAN	v191529	v1001827303	1988M1	
	(Sum)	Exports metal and other mineral products	CAN	v191531	v1001827303	1988M1	
	(Sum)	Exports metal and other mineral products	CAN	v191532	v1001827303	1988M1	
	(Sum)	Exports metal and other mineral products	CAN	v191535	v1001827303	1988M1	
82	EX_IND_EQUIP_BP_new	Exports industrial machinery, pieces and equipment	CAN	v191545	v1001827350	1988M1	5
	(Sum)	Exports industrial machinery, pieces and equipment	CAN	v191549	v1001827350	1988M1	
	(Sum)	Exports industrial machinery, pieces and equipment	CAN	v191556	v1001827350	1988M1	
83	EX_TRANSP_BP_new	Exports motor vehicules and parts	CAN	v191550	v1001827369	1988M1	5
	(Sum)	Exports motor vehicules and parts	CAN	v191551	v1001827369	1988M1	
	(Sum)	Exports motor vehicules and parts	CAN	v191552	v1001827369	1988M1	
84	EX_CONS_BP_new	Exports consumption goods	CAN	v191492	v1001827385	1988M1	5
	(Sum)	Exports consumption goods	CAN	v191534	v1001827385	1988M1	
	(Sum)	Exports consumption goods	CAN	v191547	v1001827385	1988M1	
85	IMP_METAL_BP_new	Imports metal and other mineral products	CAN	v183446	v1001826691	1988M1	5
	(Sum)	Imports metal and other mineral products	CAN	v183447	v1001826691	1988M1	
	(Sum)	Imports metal and other mineral products	CAN	v183448	v1001826691	1988M1	
	(Sum)	Imports metal and other mineral products	CAN	v183435	v1001826691	1988M1	
	(Sum)	Imports metal and other mineral products	CAN	v183436	v1001826691	1988M1	
	(Sum)	Imports metal and other mineral products	CAN	v183439	v1001826691	1988M1	
86	IMP_IND_EQUIP_BP_new	Imports industrial machinery, pieces and equipment	CAN	v183450	v1001826738	1988M1	5
	(Sum)	Imports industrial machinery, pieces and equipment	CAN	v183461	v1001826738	1988M1	
	(Sum)	Imports industrial machinery, pieces and equipment	CAN	v183465	v1001826738	1988M1	
	(Sum)	Imports industrial machinery, pieces and equipment	CAN	v183466	v1001826738	1988M1	
	(Sum)	Imports industrial machinery, pieces and equipment	CAN	v183467	v1001826738	1988M1	
	(Sum)	Imports industrial machinery, pieces and equipment	CAN	v183468	v1001826738	1988M1	
87	IMP_TRANSP_BP_new	Imports motor vehicules and parts	CAN	v183469	v1001826757	1988M1	5
	(Sum)	Imports motor vehicules and parts	CAN	v183470	v1001826757	1988M1	
	(Sum)	Imports motor vehicules and parts	CAN	v183471	v1001826757	1988M1	
88	IMP_CONS_BP_new	Imports consumption goods	CAN	v183457	v1001826773	1988M1	5
	(Sum)	Imports consumption goods	CAN	v183458	v1001826773	1988M1	
	(Sum)	Imports consumption goods	CAN	v183459	v1001826773	1988M1	
	(Sum)	Imports consumption goods	CAN	v183460	v1001826773	1988M1	
	(Sum)	Imports consumption goods	CAN	v183462	v1001826773	1988M1	
	(Sum)	Imports consumption goods	CAN	v183463	v1001826773	1988M1	
89	USDCAD_new	Exchange rate CADUSD	CAN	v37426	v111666275	2017M1	5
90	JPYCAD_new	Exchange rate CADJPY	CAN	v37456	v111666258	2017M1	5
91	GBPCAD_new	Exchange rate CADGBP	CAN	v37430	v111666274	2017M1	5
92	CAN_EQTY_NETFLOW	Canadian equity and investment fund shares, net flows	CAN	v61916203			1
93	CAN_SEC_NETFLOW	Canadian securities, Net flows	CAN	v61915649			1
94	FOR_SEC_NETFLOW	Foreign securities, Net flows	CAN	v61915715			1
95	CAN_US_SEC_NETFLOW	Canadian securities, United States, Net flows	CAN	v61915862			1
		PRICES					
96	CPI_ALL_CAN	Consumption price index (CPI) (all)	CAN	v41690973			5
97	CPI_SHEL_CAN	CPI (shelter)	CAN	v41691050			5
98	CPI_CLOT_CAN	CPI (clothing and footwear)	CAN	v41691108			5
99	CPI_HEA_CAN	CPI (health and personal care)	CAN	v41691153			5
100	CPI_MINUS_FOO_CAN	CPI (all minus food)	CAN	v41691232			5
101	CPI_MINUS_FEN_CAN	CPI (all minus food and energy)	CAN	v41691233			5
102	CPI_GOO_CAN	CPI (durable goods)	CAN	v41691223			5
103	CPI_DUR_CAN	CPI (goods)	CAN	v41691222			5
104	CPI_SERV_CAN	CPI (services)	CAN	v41691230			5
105	IPPI_CAN	Industrial production price index (IPPI) (all)	CAN	v79309114			5
106	IPPI_ENER_CAN	IPPI (energy)	CAN	v79309126			5
107	IPPI_WOOD_CAN	IPPI (wood)	CAN	v79309124			5
108	IPPI_METAL_CAN	IPPI (metal and construction materials)	CAN	v79309129			5
109	IPPI_MOTOR_CAN	IPPI (motor vehicles and parts)	CAN	v79309130			5
110	IPPI_MACH_CAN	IPPI (industrial machinery and equipment)	CAN	v79309131			5
111	WTISPLC	Petroleum price Western Intermediate (WTI) (FRED)		WTISPLC			5
		STOCK MARKETS					
112	TSX_HI	Toronto Stock Exchange (high)		v122618			5
113	TSX_LO	Toronto Stock Exchange (low)		v122619			5
114	TSX_CLO	Toronto Stock Exchange (close)		v122620			5
115	DJ_CLO	Dow Jones index (close)		v37416	DJI (YAHOO!)		5
116	SP500	Standard and Poor's (500) index (YAHOO)		GSPC			5
		PROVINCIAL / REGIONAL SERIES					
		HOUSING AND CONSTRUCTION					
117	NHOUSE_P_NF	New housing price index, Total (house and land)	NF	v111955448			5
118	NHOUSE_P_PEI	New housing price index, Total (house and land)	PEI	v111955454			5
119	NHOUSE_P_NS	New housing price index, Total (house and land)	NS	v111955460			5
120	NHOUSE_P_NB	New housing price index, Total (house and land)	NB	v111955466			5
121	NHOUSE_P_QC	New housing price index, Total (house and land)	QC	v111955472			5
122	NHOUSE_P_ONT	New housing price index, Total (house and land)	ONT	v111955490			5
123	NHOUSE_P_MAN	New housing price index, Total (house and land)	MAN	v111955526			5

No	Variable	Description	Region	Vector(1)	Vector(2)	Date	T-code
124	NHOUSE_P_SAS	New housing price index, Total (house and land)	SAS	v111955532			5
125	NHOUSE_P_ALB	New housing price index, Total (house and land)	ALB	v111955541			5
126	NHOUSE_P_BC	New housing price index, Total (house and land)	BC	v111955550			5
127	hstart_NF_new	Housing starts (units)	NF	v730402	v52300159	1990M1	2
128	hstart_PEI_new	Housing starts (units)	PEI	v730403	v52300160	1990M1	2
129	hstart_NS_new	Housing starts (units)	NS	v730404	v52300161	1990M1	5
130	hstart_NB_new	Housing starts (units)	NB	v730405	v52300162	1990M1	2
131	hstart_QC_new	Housing starts (units)	QC	v730406	v52300163	1990M1	5
132	hstart_ONT_new	Housing starts (units)	ONT	v730407	v52300164	1990M1	5
133	hstart_MAN_new	Housing starts (units)	MAN	v730409	v52300166	1990M1	2
134	hstart_SAS_new	Housing starts (units)	SAS	v730410	v52300167	1990M1	5
135	hstart_ALB_new	Housing starts (units)	ALB	v730411	v52300168	1990M1	5
136	hstart_BC_new	Housing starts (units)	BC	v730412	v52300169	1990M1	5
137	build_Total_NF_new	Building permits (tous)	NF	v42094	v121314755	2011M1	5
138	build_Ind_NF_new	Building permits (industries)	NF	v42097	v121323155	2011M1	2
139	build_Comm_NF_new	Building permits (commerce)	NF	v42098	v121326275	2011M1	5
140	build_Total_PEI_new	Building permits (tous)	PEI	v42106	v121336115	2011M1	5
141	build_Ind_PEI_new	Building permits (industries)	PEI	v42109	v121344515	2011M1	2
142	build_Comm_PEI_new	Building permits (commerce)	PEI	v42110	v121347635	2011M1	5
143	build_Total_NS_new	Building permits (tous)	NS	v42112	v121357475	2011M1	5
144	build_Ind_NS_new	Building permits (industries)	NS	v42115	v121365875	2011M1	5
145	build_Comm_NS_new	Building permits (commerce)	NS	v42116	v121368995	2011M1	5
146	build_Total_NB_new	Building permits (tous)	NB	v42118	v121378835	2011M1	5
147	build_Ind_NB_new	Building permits (industries)	NB	v42122	v121387235	2011M1	2
148	build_Comm_NB_new	Building permits (commerce)	NB	v42123	v121390355	2011M1	5
149	build_Total_QC_new	Building permits (tous)	QC	v42163	v121400195	2011M1	5
150	build_Ind_QC_new	Building permits (industries)	QC	v42166	v121408595	2011M1	5
151	build_Comm_QC_new	Building permits (commerce)	QC	v42167	v121411715	2011M1	5
152	build_Total_ONT_new	Building permits (tous)	ONT	v42199	v121421555	2011M1	5
153	build_Ind_ONT_new	Building permits (industries)	ONT	v42202	v121429955	2011M1	5
154	build_Comm_ONT_new	Building permits (commerce)	ONT	v42203	v121433075	2011M1	5
155	build_Total_MAN_new	Building permits (tous)	MAN	v42124	v121442915	2011M1	5
156	build_Ind_MAN_new	Building permits (industries)	MAN	v42128	v121451315	2011M1	5
157	build_Comm_MAN_new	Building permits (commerce)	MAN	v42129	v121454435	2011M1	5
158	build_Total_SAS_new	Building permits (tous)	SAS	v42130	v121464275	2011M1	5
159	build_Ind_SAS_new	Building permits (industries)	SAS	v42133	v121472675	2011M1	5
160	build_Comm_SAS_new	Building permits (commerce)	SAS	v42134	v121475795	2011M1	5
161	build_Total_ALB_new	Building permits (tous)	ALB	v42136	v121485635	2011M1	5
162	build_Ind_ALB_new	Building permits (industries)	ALB	v42139	v121494035	2011M1	5
163	build_Comm_ALB_new	Building permits (commerce)	ALB	v42140	v121497155	2011M1	5
164	build_Total_BC_new	Building permits (tous)	BC	v42250	v121506995	2011M1	5
165	build_Ind_BC_new	Building permits (industries)	BC	v42253	v121515395	2011M1	5
166	build_Comm_BC_new	Building permits (commerce)	BC	v42254	v121518515	2011M1	5
		LABOR MARKET					
167	EMP_NF	Employment total	NF	v2057622			5
168	EMP_SERV_NF	Employment services	NF	v2057629			5
169	EMP_FOR_OIL_NF	Employment forestry, fishing, mining, oil and gas	NF	v2057625			5
170	EMP_CONS_NF	Employment construction	NF	v2057627			5
171	EMP_SALES_NF	Employment sales (wholesale and retail trade)	NF	v2057630			5
172	EMP_FIN_NF	Employment finance, insurance and real estate	NF	v2057632			5
173	EMP_MANU_NF	Employment manufacturing	NF	v2057628			5
174	EMP_PEI	Employment total	PEI	v2057641			5
175	EMP_SERV_PEI	Employment services	PEI	v2057648			5
176	EMP_FOR_OIL_PEI	Employment forestry, fishing, mining, oil and gas	PEI	v2057644			5
177	EMP_CONS_PEI	Employment construction	PEI	v2057646			5
178	EMP_SALES_PEI	Employment sales (wholesale and retail trade)	PEI	v2057649			5
179	EMP_FIN_PEI	Employment finance, insurance and real estate	PEI	v2057651			5
180	EMP_MANU_PEI	Employment manufacturing	PEI	v2057647			5
181	EMP_NS	Employment total	NS	v2057660			5
182	EMP_SERV_NS	Employment services	NS	v2057667			5
183	EMP_FOR_OIL_NS	Employment forestry, fishing, mining, oil and gas	NS	v2057663			5
184	EMP_CONS_NS	Employment construction	NS	v2057665			5
185	EMP_SALES_NS	Employment sales (wholesale and retail trade)	NS	v2057668			5
186	EMP_FIN_NS	Employment finance, insurance and real estate	NS	v2057670			5
187	EMP_MANU_NS	Employment manufacturing	NS	v2057666			5
188	EMP_NB	Employment total	NB	v2057679			5
189	EMP_SERV_NB	Employment services	NB	v2057686			5
190	EMP_FOR_OIL_NB	Employment forestry, fishing, mining, oil and gas	NB	v2057682			5
191	EMP_CONS_NB	Employment construction	NB	v2057684			5
192	EMP_SALES_NB	Employment sales (wholesale and retail trade)	NB	v2057687			5
193	EMP_FIN_NB	Employment finance, insurance and real estate	NB	v2057689			5
194	EMP_MANU_NB	Employment manufacturing	NB	v2057685			5
195	EMP_QC	Employment total	QC	v2057698			5
196	EMP_SERV_QC	Employment services	QC	v2057705			5
197	EMP_FOR_OIL_QC	Employment forestry, fishing, mining, oil and gas	QC	v2057701			5
198	EMP_CONS_QC	Employment construction	QC	v2057703			5
199	EMP_SALES_QC	Employment sales (wholesale and retail trade)	QC	v2057706			5
200	EMP_FIN_QC	Employment finance, insurance and real estate	QC	v2057708			5
201	EMP_MANU_QC	Employment manufacturing	QC	v2057704			5
202	EMP_ONT	Employment total	ONT	v2057717			5
203	EMP_SERV_ONT	Employment services	ONT	v2057724			5
204	EMP_FOR_OIL_ONT	Employment forestry, fishing, mining, oil and gas	ONT	v2057720			5
205	EMP_CONS_ONT	Employment construction	ONT	v2057722			5
206	EMP_SALES_ONT	Employment sales (wholesale and retail trade)	ONT	v2057725			5
207	EMP_FIN_ONT	Employment finance, insurance and real estate	ONT	v2057727			5
208	EMP_MANU_ONT	Employment manufacturing	ONT	v2057723			5
209	EMP_MAN	Employment total	MAN	v2057736			5
210	EMP_SERV_MAN	Employment services	MAN	v2057743			5
211	EMP_FOR_OIL_MAN	Employment forestry, fishing, mining, oil and gas	MAN	v2057739			5
212	EMP_CONS_MAN	Employment construction	MAN	v2057741			5
213	EMP_SALES_MAN	Employment sales (wholesale and retail trade)	MAN	v2057744			5
214	EMP_FIN_MAN	Employment finance, insurance and real estate	MAN	v2057746			5
215	EMP_MANU_MAN	Employment manufacturing	MAN	v2057742			5
216	EMP_SAS	Employment total	SAS	v2057755			5
217	EMP_SERV_SAS	Employment services	SAS	v2057762			5

No	Variable	Description	Region	Vector(1)	Vector(2)	Date	T-code
218	EMP_FOR_OIL_SAS	Employment forestry, fishing, mining, oil and gas	SAS	v2057758			5
219	EMP_CONS_SAS	Employment construction	SAS	v2057760			5
220	EMP_SALES_SAS	Employment sales (wholesale and retail trade)	SAS	v2057763			5
221	EMP_FIN_SAS	Employment finance, insurance and real estate	SAS	v2057765			5
222	EMP_MANU_SAS	Employment manufacturing	SAS	v2057761			5
223	EMP_ALB	Employment total	ALB	v2057774			5
224	EMP_SERV_ALB	Employment services	ALB	v2057781			5
225	EMP_FOR_OIL_ALB	Employment forestry, fishing, mining, oil and gas	ALB	v2057777			5
226	EMP_CONS_ALB	Employment construction	ALB	v2057779			5
227	EMP_SALES_ALB	Employment sales (wholesale and retail trade)	ALB	v2057782			5
228	EMP_FIN_ALB	Employment finance, insurance and real estate	ALB	v2057784			5
229	EMP_MANU_ALB	Employment manufacturing	ALB	v2057780			5
230	EMP_BC	Employment total	BC	v2057793			5
231	EMP_SERV_BC	Employment services	BC	v2057800			5
232	EMP_FOR_OIL_BC	Employment forestry, fishing, mining, oil and gas	BC	v2057796			5
233	EMP_CONS_BC	Employment construction	BC	v2057798			5
234	EMP_SALES_BC	Employment sales (wholesale and retail trade)	BC	v2057801			5
235	EMP_FIN_BC	Employment finance, insurance and real estate	BC	v2057803			5
236	EMP_MANU_BC	Employment manufacturing	BC	v2057799			5
237	UNEMP_NF	Unemployment rate	NF	v2063004			2
238	UNEMP_PEI	Unemployment rate	PEI	v2063193			2
239	UNEMP_NS	Unemployment rate	NS	v2063382			2
240	UNEMP_NB	Unemployment rate	NB	v2063571			2
241	UNEMP_QC	Unemployment rate	QC	v2063760			2
242	UNEMP_ONT	Unemployment rate	ONT	v2063949			2
243	UNEMP_MAN	Unemployment rate	MAN	v2064138			2
244	UNEMP_SAS	Unemployment rate	SAS	v2064327			2
245	UNEMP_ALB	Unemployment rate	ALB	v2064516			2
246	UNEMP_BC	Unemployment rate	BC	v2064705			2
247	EMP_PART_NF	Employment part time	NF	v2063002			5
248	EMP_PART_PEI	Employment part time	PEI	v2063191			5
249	EMP_PART_NS	Employment part time	NS	v2063380			5
250	EMP_PART_NB	Employment part time	NB	v2063569			5
251	EMP_PART_QC	Employment part time	QC	v2063758			5
252	EMP_PART_ONT	Employment part time	ONT	v2063947			5
253	EMP_PART_MAN	Employment part time	MAN	v2064136			5
254	EMP_PART_SAS	Employment part time	SAS	v2064325			5
255	EMP_PART_ALB	Employment part time	ALB	v2064514			5
256	EMP_PART_BC	Employment part time	BC	v2064703			5
257	UNEMP_DURAvg_NF_new	Unemployment average duration	NF	v3434211	v1078669579		5
258	UNEMP_DURAvg_PEI_new	Unemployment average duration	PEI	v3434535	v1078670767		5
259	UNEMP_DURAvg_NS_new	Unemployment average duration	NS	v3434859	v1078671955		5
260	UNEMP_DURAvg_NB_new	Unemployment average duration	NB	v3435183	v1078673143		5
261	UNEMP_DURAvg_QC_new	Unemployment average duration	QC	v3435507	v1078674331		5
262	UNEMP_DURAvg_ONT_new	Unemployment average duration	ONT	v3435831	v1078675519		5
263	UNEMP_DURAvg_MAN_new	Unemployment average duration	MAN	v3436155	v1078676707		5
264	UNEMP_DURAvg_SAS_new	Unemployment average duration	SAS	v3436479	v1078677895		5
265	UNEMP_DURAvg_ALB_new	Unemployment average duration	ALB	v3436803	v1078679083		5
266	UNEMP_DURAvg_BC_new	Unemployment average duration	BC	v3437127	v1078680271		5
267	CLAIMS_NF	Employment insurance initial claims, Allowed	NF	v383943			1
268	CLAIMS_PEI	Employment insurance initial claims, Allowed	PEI	v383948			1
269	CLAIMS_NS	Employment insurance initial claims, Allowed	NS	v383949			1
270	CLAIMS_NB	Employment insurance initial claims, Allowed	NB	v383950			1
271	CLAIMS_QC	Employment insurance initial claims, Allowed	QC	v383951			1
272	CLAIMS_ONT	Employment insurance initial claims, Allowed	ONT	v383952			1
273	CLAIMS_MAN	Employment insurance initial claims, Allowed	MAN	v383953			1
274	CLAIMS_SAS	Employment insurance initial claims, Allowed	SAS	v383954			1
275	CLAIMS_ALB	Employment insurance initial claims, Allowed	ALB	v383955			1
276	CLAIMS_BC	Employment insurance initial claims, Allowed	BC	v383944			1
		MANUFACTURING, SALES AND INVENTORIES					
277	MANU_NF_new	Manufacturing new orders (total)	NF	v727515	v803786	1992M1	5
278	DUR_NF_new	Manufacturing new orders (durables)	NF	v727527	v803799	1992M1	5
279	MANU_PEI_new	Manufacturing new orders (total)	PEI	v727539	v804246	1992M1	5
280	DUR_PEI_new	Manufacturing new orders (durables)	PEI	v727551	v804259	1992M1	5
281	MANU_NS_new	Manufacturing new orders (total)	NS	v727563	v804706	1992M1	5
282	DUR_NS_new	Manufacturing new orders (durables)	NS	v727577	v804719	1992M1	5
283	MANU_NB_new	Manufacturing new orders (total)	NB	v727591	v805166	1992M1	5
284	DUR_NB_new	Manufacturing new orders (durables)	NB	v727605	v805179	1992M1	5
285	MANU_QC_new	Manufacturing new orders (total)	QC	v727617	v805626	1992M1	5
286	DUR_QC_new	Manufacturing new orders (durables)	QC	v727632	v805639	1992M1	5
287	MANU_ONT_new	Manufacturing new orders (total)	ONT	v727646	v806086	1992M1	5
288	DUR_ONT_new	Manufacturing new orders (durables)	ONT	v727661	v806099	1992M1	5
289	MANU_MAN_new	Manufacturing new orders (total)	MAN	v727675	v806546	1992M1	5
290	DUR_MAN_new	Manufacturing new orders (durables)	MAN	v727689	v806559	1992M1	5
291	MANU_SAS_new	Manufacturing new orders (total)	SAS	v727703	v807006	1992M1	5
292	DUR_SAS_new	Manufacturing new orders (durables)	SAS	v727716	v807019	1992M1	5
293	MANU_ALB_new	Manufacturing new orders (total)	ALB	v727729	v807466	1992M1	5
294	DUR_ALB_new	Manufacturing new orders (durables)	ALB	v727743	v807479	1992M1	5
295	MANU_BC_new	Manufacturing new orders (total)	BC	v727756	v807928	1992M1	5
296	DUR_BC_new	Manufacturing new orders (durables)	BC	v727770	v807941	1992M1	5
		PRICES					
297	CPI_ALL_NF	Consumption price index (CPI) (all)	NF	v41691244			5
298	CPI_SHEL_NF	CPI (shelter)	NF	v41691277			5
299	CPI_CLOT_NF	CPI (clothing and footwear)	NF	v41691304			5
300	CPI_HEA_NF	CPI (health and personal care)	NF	v41691328			5
301	CPI_MINUS_FOO_NF	CPI (all minus food)	NF	v41691368			5
302	CPI_MINUS_FEN_NF	CPI (all minus food and energy)	NF	v41691369			5
303	CPI_GOO_NF	CPI (goods)	NF	v41691363			5
304	CPI_DUR_NF	CPI (durable goods)	NF	v41691364			5
305	CPI_SERV_NF	CPI (services)	NF	v41691367			5
306	CPI_ALL_PEI	Consumption price index (CPI) (all)	PEI	v41691379			5
307	CPI_SHEL_PEI	CPI (shelter)	PEI	v41691412			5
308	CPI_CLOT_PEI	CPI (clothing and footwear)	PEI	v41691439			5
309	CPI_HEA_PEI	CPI (health and personal care)	PEI	v41691462			5
310	CPI_MINUS_FOO_PEI	CPI (all minus food)	PEI	v41691502			5

No	Variable	Description	Region	Vector(1)	Vector(2)	Date	T-code
311	CPI_MINUS_FEN_PEI	CPI (all minus food and energy)	PEI	v41691503			5
312	CPI_GOO_PEI	CPI (goods)	PEI	v41691497			5
313	CPI_DUR_PEI	CPI (durable goods)	PEI	v41691498			5
314	CPI_SERV_PEI	CPI (services)	PEI	v41691501			5
315	CPI_ALL_NS	Consumption price index (CPI) (all)	NS	v41691513			5
316	CPI_SHEL_NS	CPI (shelter)	NS	v41691546			5
317	CPI_CLOT_NS	CPI (clothing and footwear)	NS	v41691573			5
318	CPI_HEA_NS	CPI (health and personal care)	NS	v41691597			5
319	CPI_MINUS_FOO_NS	CPI (all minus food)	NS	v41691637			5
320	CPI_MINUS_FEN_NS	CPI (all minus food and energy)	NS	v41691638			5
321	CPI_GOO_NS	CPI (goods)	NS	v41691632			5
322	CPI_DUR_NS	CPI (durable goods)	NS	v41691633			5
323	CPI_SERV_NS	CPI (services)	NS	v41691636			5
324	CPI_ALL_NB	Consumption price index (CPI) (all)	NB	v41691648			5
325	CPI_SHEL_NB	CPI (shelter)	NB	v41691681			5
326	CPI_CLOT_NB	CPI (clothing and footwear)	NB	v41691708			5
327	CPI_HEA_NB	CPI (health and personal care)	NB	v41691732			5
328	CPI_MINUS_FOO_NB	CPI (all minus food)	NB	v41691772			5
329	CPI_MINUS_FEN_NB	CPI (all minus food and energy)	NB	v41691773			5
330	CPI_GOO_NB	CPI (goods)	NB	v41691767			5
331	CPI_DUR_NB	CPI (durable goods)	NB	v41691768			5
332	CPI_SERV_NB	CPI (services)	NB	v41691771			5
333	CPI_ALL_QC	Consumption price index (CPI) (all)	QC	v41691783			5
334	CPI_SHEL_QC	CPI (shelter)	QC	v41691816			5
335	CPI_CLOT_QC	CPI (clothing and footwear)	QC	v41691844			5
336	CPI_HEA_QC	CPI (health and personal care)	QC	v41691868			5
337	CPI_MINUS_FOO_QC	CPI (all minus food)	QC	v41691908			5
338	CPI_MINUS_FEN_QC	CPI (all minus food and energy)	QC	v41691909			5
339	CPI_GOO_QC	CPI (goods)	QC	v41691903			5
340	CPI_DUR_QC	CPI (durable goods)	QC	v41691904			5
341	CPI_SERV_QC	CPI (services)	QC	v41691907			5
342	CPI_ALL_ONT	Consumption price index (CPI) (all)	ONT	v41691919			5
343	CPI_SHEL_ONT	CPI (shelter)	ONT	v41691952			5
344	CPI_CLOT_ONT	CPI (clothing and footwear)	ONT	v41691980			5
345	CPI_HEA_ONT	CPI (health and personal care)	ONT	v41692004			5
346	CPI_MINUS_FOO_ONT	CPI (all minus food)	ONT	v41692044			5
347	CPI_MINUS_FEN_ONT	CPI (all minus food and energy)	ONT	v41692045			5
348	CPI_GOO_ONT	CPI (goods)	ONT	v41692039			5
349	CPI_DUR_ONT	CPI (durable goods)	ONT	v41692040			5
350	CPI_SERV_ONT	CPI (services)	ONT	v41692043			5
351	CPI_ALL_MAN	Consumption price index (CPI) (all)	MAN	v41692055			5
352	CPI_SHEL_MAN	CPI (shelter)	MAN	v41692088			5
353	CPI_CLOT_MAN	CPI (clothing and footwear)	MAN	v41692116			5
354	CPI_HEA_MAN	CPI (health and personal care)	MAN	v41692140			5
355	CPI_MINUS_FOO_MAN	CPI (all minus food)	MAN	v41692180			5
356	CPI_MINUS_FEN_MAN	CPI (all minus food and energy)	MAN	v41692181			5
357	CPI_GOO_MAN	CPI (goods)	MAN	v41692175			5
358	CPI_DUR_MAN	CPI (durable goods)	MAN	v41692176			5
359	CPI_SERV_MAN	CPI (services)	MAN	v41692179			5
360	CPI_ALL_SAS	Consumption price index (CPI) (all)	SAS	v41692191			5
361	CPI_SHEL_SAS	CPI (shelter)	SAS	v41692224			5
362	CPI_CLOT_SAS	CPI (clothing and footwear)	SAS	v41692252			5
363	CPI_HEA_SAS	CPI (health and personal care)	SAS	v41692276			5
364	CPI_MINUS_FOO_SAS	CPI (all minus food)	SAS	v41692316			5
365	CPI_MINUS_FEN_SAS	CPI (all minus food and energy)	SAS	v41692317			5
366	CPI_GOO_SAS	CPI (goods)	SAS	v41692311			5
367	CPI_DUR_SAS	CPI (durable goods)	SAS	v41692312			5
368	CPI_SERV_SAS	CPI (services)	SAS	v41692315			5
369	CPI_ALL_ALB	Consumption price index (CPI) (all)	ALB	v41692327			5
370	CPI_SHEL_ALB	CPI (shelter)	ALB	v41692360			5
371	CPI_CLOT_ALB	CPI (clothing and footwear)	ALB	v41692387			5
372	CPI_HEA_ALB	CPI (health and personal care)	ALB	v41692411			5
373	CPI_MINUS_FOO_ALB	CPI (all minus food)	ALB	v41692451			5
374	CPI_MINUS_FEN_ALB	CPI (all minus food and energy)	ALB	v41692452			5
375	CPI_GOO_ALB	CPI (goods)	ALB	v41692446			5
376	CPI_DUR_ALB	CPI (durable goods)	ALB	v41692447			5
377	CPI_SERV_ALB	CPI (services)	ALB	v41692450			5
378	CPI_ALL_BC	Consumption price index (CPI) (all)	BC	v41692462			5
379	CPI_SHEL_BC	CPI (shelter)	BC	v41692495			5
380	CPI_CLOT_BC	CPI (clothing and footwear)	BC	v41692523			5
381	CPI_HEA_BC	CPI (health and personal care)	BC	v41692547			5
382	CPI_MINUS_FOO_BC	CPI (all minus food)	BC	v41692587			5
383	CPI_MINUS_FEN_BC	CPI (all minus food and energy)	BC	v41692588			5
384	CPI_GOO_BC	CPI (goods)	BC	v41692582			5
385	CPI_DUR_BC	CPI (durable goods)	BC	v41692583			5
386	CPI_SERV_BC	CPI (services)	BC	v41692586			5