Estimating and Forecasting Employment Insurance Claims in Canada

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Major Paper

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Table of Contents

Abstract

Future demand for Employment Insurance (EI) benefits is a matter of primary concern for Service Canada due to its potential impact on the workload and the quality of service delivery of the EI program. Consequently, adequate projections of the number of EI claims is an important research subject from both methodological and policy perspectives. This study estimates a number of univariate ARIMA and multivariate VAR/VEC forecasting models, and a few forecast combination procedures for their predictive ability over selected short-term and medium-term horizons in Canada and its provinces. The evaluation of forecasting performance highlights the predictive improvements from the multivariate VAR/VEC framework with respect to the benchmark ARIMA. It also indicates the effectiveness of forecast pooling strategies in the presence of structural breaks and near-integration. In addition, the results suggest the positive impact of co-integration relations and emphasize the adverse effects of structural changes, data variability, and time-dependent persistence on the quality of forecasts. Finally, policy implications with respect to the projected demand for EI benefits are discussed.

1. Introduction

The recent slowdown of the global economy and the massive retirement from the baby boom generation has led to a large increase in the volume of Employment Insurance (EI) / Canadian Pension Plan (CPP) / Old Age Security (OAS) claims. Consequently, Service Canada is facing a great challenge to maintain an adequate level of service delivery. On one hand, the current widespread unemployment and retirement waves induce a growing demand for public service provisions, which inevitably imposes a rising cost to the EI/CPP/OAS programs. On the other hand, it also causes shortfalls in fiscal revenue in terms of income tax payables and program premiums, which force the federal government to increasingly tighten its budget. Thus, the need for Service Canada to derive optimal strategies to serve Canadians within a reasonable processing time with lowest risk of processing errors and reduced fraud has become more critical than ever (see CEIC, 2010, section 1.1 and section 4.2).

Indeed, trends in demand for public service provisions have a important influence on the two main facets of the service delivery system: the cost and the quality. A good forecasting model for the number of EI/CPP/OAS claims can identify a variety of endogenous/exogenous factors that exert perceptible impacts on the demand side, which subsequently affects the workload management and the service delivery performance of the respective program (EI/CPP/OAS). Reliable predictions can provide useful guidelines for program administrators to ensure adequate allocation of resources and public funds in order to meet anticipated demand for EI/CPP/OAS benefits. In addition, accurate projection of the future volume of EI/CPP/OAS applicants is also necessary for policy makers to estimate the potential effects of a policy change with respect to the cost and the quality of these programs (see Mahalingam, 2008).

This study is exclusively concerned with the evolution in the demand for EI benefits, including both initial and renewal claims. The reason for this choice is primarily two-fold. First, data for the EI claims are made publicly available by Statistics Canada, whereas the number of CPP/OAS applicants can only be extracted from the administrative data of Human Resources and Skills Development Canada (HRSDC). Second, the presence of irregular characteristics in the data renders the estimation and the forecasting of EI claims much more challenging than other macroeconomic variables.

Figure 1 in Appendix A presents the overlay plot of the monthly, seasonally adjusted series of EI claims and the unemployment rates over the period from January, 1997 to February, 2011 in Canada and Quebec. In fact, the unemployment rates series is one of the labour market indicators closely related to the volume of EI claims (see CEIC, 2010, section 1.3). As we can see, even though these two variables look like they are comoving through time, the two EI claim series are characterized by profound structural changes and large variability, which are much more obvious than in their unemployment rates counterparts. Structural breaks, particularly during the two fiscal years 2008-2009 and 2009-2010, appear to be most accentuated in Canada as a whole, where we can observe a dramatic increase in the number of filers from 212,560 in February, 2008 to 327,700 in May, 2009, followed by a sudden reversal to 230,170 in March, 2010. In contrast, Quebec experiences substantial data variability. For example, within four consecutive months, there is a deep drop from 72,860 claims in November to 59,950 claims in December, 2006, followed by a sharp rise up to 79,430 claims in January, and a subsequent abrupt decline to 64,920 claims in February, 2007. Note that unlike the unemployment rates, the demand for EI benefits is not only affected by the overall macroeconomic conditions but also by EI-program-specific policy interventions. Furthermore, visual examination of the correlograms in Figure 2, Appendix A also suggests the existence of near-integration in the two EI claim series, whose respective correlograms decay much slower than a true stationary process but much faster than a typical non-stationary one like the GDP (see Figure 2 in Appendix A).

It has long been known in the literature that structural breaks and large variability may cause significant shifts in means and inflate standard deviations. These conditions, if not properly treated, may lead to instability in parameter estimates and distort the regression lines (see Clements and Hendry, 2006). On the other hand, near-integrated variables are likely to induce spurious regression results because they tend to behave like integrated processes (see Hjalmarsson and Österholm, 2007). As such, the combination of these three characteristics in the data makes it much more difficult to generate reliable estimates and forecasts for EI claims as compared to their unemployment rate counterparts.

The objective of this study is to produce up to one year projections of the total EI applications received at the national and regional levels on the basis of time series analysis. A univariate ARIMA model will be identified to serve as the baseline model against which a number of multivariate VAR/VEC models will be estimated and assessed for their forecasting performance. Finally, a set of forecast combination strategies will be explored in order to evaluate their ability to enhance the quality of predictions in the presence of structural changes and near-integration. The most suitable forecasting methodology will be identified to provide short-term and medium-term forecasts of the EI claim levels. This, in turn, will help to examine the effect of predicted changes in EI demand on various components of the EI service delivery system such as resource requirements, processing time, etc.

The remainder of this paper is laid out as follows. Section 2 provides a brief overview of Employment Insurance. Section 3 reviews the range of time series modeling techniques that have been developed in the literature to forecast EI/UI claims or other related labour market variables such as unemployment rates, employment rates, etc. Section 4 outlines the modeling methodology applied in this study. Section 5 states the data sources and describes the data transformations. Section 6 reports the empirical results including both in-sample analysis and out-of-sample evaluation. Section 7 discusses policy implications of the findings. Section 8 presents conclusing remarks and directions for future research. Appendices at the end of the paper include tables and graphs to illustrate the result analysis.

2. Background of the Employment Insurance[1]

The EI is a federal income security program administered by HRSDC. The program was first established in 1940, under the name "*Unemployment Insurance*" (UI) and offers only a limited coverage of the labour force. Since then, it has constantly evolved through numerous and significant legislative amendments. The 1971 reform substantially altered the UI structure with a generous expansion of program coverage, relaxing of eligibility criteria, and widening of the range of special benefits. These measures, coupled with the economic downturn during the period 1980-1993, resulted in considerable annual budget deficits (see Lin, 1998, section 3).

From 1976-1996, the UI system was subjected to a series of refining program parameters and the enforcement of eligibility rules as a reaction to the climbing financial costs. These included the enlargement of coverage for working-age population in an effort to broaden the base of contributions, the reduction of maximum age for coverage, maximum benefits amount/duration, wage replacement rate, and the qualification

[1] Refer to CEIC (2009), Makarenko (2009) and Lin (1998) for more details on the historical evolution of the EI program.

period. The Variable Entrance Requirements (VERs) to ease entrance requirements and flatten benefit duration in regions with high unemployment rates was introduced but subsequently trimmed. Benefit repayment (i.e. "*clawback*") was imposed on repeat recipients with high income, together with the modification of special benefits, the strengthening of fraud penalties, and the lengthening of disqualification/disentitlement period (see Lin, 1998, section 2 and 3).

These structural measures together with a strong economic recovery during the mid 1990s had turned the program deficits into balance in 1993, followed by large annual surpluses since 1994. The UI system was renamed to "*Employment Insurance*" in 1996 to emphasize its primary goal of targeting long-term employment rather than tackling short-term unemployment. A new system of accounting was implemented such that entrance criteria and benefit entitlement became hourly-based rather than weekly-based. Allowable Earnings While on Claim Provision was introduced to encourage labour force attachment. Rules on the benefit duration, benefit repayment, disqualification period, and rules for entrance/reentrance/intensity were further tightened up and enforced (see (see Lin, 1998, section 3 and CEIC, 2010, Annex 6.1).

The program continued to undergo several additional fine-tunings with the extension of parental benefit from 10 to 35 weeks in 2000, the abandoning of the intensity rule, the lengthening of special benefits' duration in 2002, the availability of Compassionate Care Benefits in 2003 to support workers who take temporary leave to care for a family member suffering from deadly illness or injury. The Canada Employment Insurance Financing Board (CEIFB) was established in 2008 to assist HRSDC in managing the EI program and the EI account. Enhanced EI benefits and increased training opportunities were provided as part of temporary EI measures during the 2009-2010 and 2010-2011 fiscal years through Canada's Economic Action Plan (EAP) (see CEIC, 2010, Annex 6.1).

The current Employment Insurance program consists of two main components. First, the income benefits consist of short-term interventions offering temporary financial assistance to Canadians facing work termination (Regular Benefit), interrupting their employment due to special circumstances (Special Benefits), or being a self-employed fisher (Fisher Benefit).[2] Second, employment benefits consist of long-term measures

[2] See "*Employment Insurance*", Service Canada. Available on-line at http://www.servicecanada.gc.ca/eng/sc/ei/index.shtml

to promote employment for Canadians, while support measures include a range of services focusing on job search assistance and enhancement of labour force productivity/participation (see CEIC, 2010, Annex 3.3).

With the global recession ongoing since 2008 in conjunction with temporary stimulus funding from the EAP in the 2009-2010 fiscal year, the number of EI claims has skyrocketed and reached an unprecedented peak since 1996 at the end of 2008. As a consequence, the EI system has since been incurring annual deficits, which are projected to peak at $10.7 billion in 2011 before gradually being pushed down to near book balance at $0.7 billion by the end of 2014 through premium rate adjustment measures (see Danforth, 2010).

3. Literature Review

To the best of my knowledge, there have been very few forecasting studies on EI/UI claims. In fact, the majority of forecasters are concerned more often about trends in financial, macroeconomic, and labour market indicators. The rest of this section provides a brief review of the overall spectrum of alternative econometric approaches and associated methodological issues that exist in the recent forecasting literature for macroeconomic related time series.

In setting out my methodology for this particular application, it is worth mentioning the empirical work of Marcellino (2006), which provides extensive comparison of the relative forecasting performance of linear, non-linear, and time-varying models for roughly 500 macroeconomic variables from different Euro countries. According to his findings, *"the linear models work well for about 35% of the series under analysis, time-varying models for another 35% and non-linear models for the remaining 30% of the series"* (see Marcellino, 2006, Abstract). He also emphasizes that the benchmark univariate autoregressive (AR) models dominate, on average, other competitors when applied to all variables. Kurita (2010) empirically justifies for the choice of the fractional integrated autoregressive moving average (FARIMA) modeling framework, which can lead to remarkable forecasting success if the series of concern displays long and persistent memory characteristics, as in the cases of the Japanese unemployment rates.

Non-linear modeling methodologies have been motivated by the failure of their linear counterpart to account for non-linear dynamic characteristics such as time-variant volatility, irregular fluctuations, structural breaks, higher-moment structures often observed in macroeconomic variables. Yet, the major drawback is that it requires large sample size to ensure the reliability of model specifications and the accuracy of forecasts (see Kunst, 2009, section 3.4). Montgomery et al. (1998) exploit the cyclical asymmetries in US unemployment rates to build a variety non-linear forecasting classes, which are claimed to have an overall predictive superiority over other linear competitors commonly used in the literature.

Nevertheless, the effectiveness of non-linear modeling in time series analysis remains controversial. Through Monte Carlo simulations, Bessec and Bouabdallah (2005) observe better in-sample fits of non-linear alternatives in the presence of asymmetries or structural breaks. Yet, they may not offer much forecasting advantage relative to their linear counterparts, especially at long forecast horizons. As a consequence of large uncertainty regarding the patterns of future regimes, it is often difficult to correctly specify the state variables or the transitional probabilities. In reviewing various theoretical and empirical aspects of non-linear time series modeling as well as recent developments in this area, Clements et al. (2004) assert that the specification, the estimation and the testing of non-linear models requires cautious considerations in order to obtain substantial improvement in forecast precisions.

Several studies adopt multivariate modeling approaches in forecasting macroeconomic time series. The Vector Autoregressive Moving Average (VARMA) approach is typically useful in modeling and predicting multiple macroeconomic series based on the theoretical grounds of their mutual feedback or interdependence. Nevertheless, VARMA modeling often faces the problem of over-parameterization, also known as "*the curse of dimensionality*", in the sense that the inclusion of lagged values leads to parameter explosion as new variables are added. Quick reduction in degrees of freedom will increase the risk of multi-colinearity and expose the model predictions to greater uncertainty (see Cai, 2009, section 7.4). Yet, a VARMA model of low order may suffer from omitted variable bias and yield spurious significance of parameter estimates (see Stock and Watson, 2001). As such, VARMAs do not necessarily generate better forecasts than their ARIMA counterparts unless much caution has been devoted to derive the right specification (see Kunst 2009, section 4). Stock and Watson (2001) examine the forecast reliability of a three-variable VAR consisting of unemployment rates, interest rates and inflation rates. This particular model exhibits neither superiority nor inferiority vis-à-vis the AR baseline.

To further enhance the predictive quality, the basic ARIMA/VARMA specifications can be augmented to include exogenous cyclical indicators, often referred to as ARIMAX/VARMAX, in order to exploit the dynamic aspects that do not present in the series in question. However, model efficiency and stability may be compromised if several indicators are chosen, as both their lagged and present values may be included (see Fauvel et al., 1999, p 10-11). Contrary to the ARIMA/VARMA framework, where all variables are treated as endogenous, forecasting from ARIMAX/VARMAX requires the extrapolation of input variables, which involves highly subjective assumptions about their future behaviour. Thus, the use of indicator variables may increase the uncertainty of model predictions (see Kunst, section 4). To mention one illustration, Fauvel et al. (1999) conduct short-term forecasting comparisons among three competing classes: ARIMA, VAR, and ARX to predict the Canadian employment at the national and the provincial levels. They conclude that VAR models are generally more effective in forecasting. Another example is Choi and Varian (2009), who empirically show the strong predictive power of the Google Job Search index with respect to UI claims in the US.

From a technical perspective, if the VAR contains only stationary processes, it can be formulated in levels (i.e. LVAR); otherwise, it should be employed in first differences (i.e. DVAR) to address spurious regression induced by non-stationarity. Yet, in the case of cointegration among integrated component series, the Vector Error Correction Model (VECM) may be more effective because of its significantly enhanced forecasting abilities at longer horizons by coupling short-run transitional dynamics with long-run interactions between interrelated economic factors (see Kunst, 2009, section 4). To consider one illustration, Wong et al. (2007) establish a VECM for Manpower demand in Hong Kong using five cointegrated labour market variables: construction output, real wages, material prices, bank rate, and labour productivity. This model is found to be statistically robust and efficient for forecasting purposes.

Other studies have been devoted to extending non-linear modeling into multivariate systems (see Milas and Rothman, 2007) with promising forecasting results in the presence of structural shifts. If the system involves long-range dependence processes, the regime-dependent fractionally integrated VARMA/VEC is then suggested (see Haldrupy et al., 2009). However, several additive complexities surrounding the structure of multivariate models make these generalization procedures much more complicated relative to the univariate forms (see Kunst, 2009, section 4).

Forecast combination has attracted a growing attention from forecasters. Empirical results often support the effectiveness of these methodologies, which are envisaged as reliable ways to pool diversified information from numerous potentially relevant predictors. Forecast combination strategies have been statistically proven to systematically dominate the single best model, specifically in the presence of substantial parameter instability induced by non-stationarity, structural changes, and/or model uncertainty caused by misspecification and/or measurement error bias (see Timmermann, 2006).[3] As an illustrative example, Talwar and Chambers (1993) apply the hybrid methodology of pooling forecasts from a number of linear univariate and multivariate regression models for a set of commonly chosen macroeconomic indicators. The resulting aggregate predictions are shown to be superior to those produced by the Conference Board of Canada in the majority of cases. More surprisingly, the simplest combination algorithms such as the simple average with equal weights or the median, which ignore the correlation between forecast errors, often outperform more sophisticated schemes, provided the underlying assumptions of a quadratic loss function (i.e. MSE) and Gaussian distributions of forecast errors are not seriously violated. They have so far served as benchmarks that are hard to surpass in the forecasting literature (see Elliott and Timmermann, 2004).

On the basis of exploring various alternative methodologies, it seems now preferable to me to focus on some linear univariate and multivariate approaches adopted by the two Canadian studies, Talwar and Chambers (1993) and Fauvel et al. (1999). As mentioned earlier, the former conduct forecasting exercises on a set of seven provincial macroeconomic variables, including UI initial and renewal claims, while the latter provide predictions of employment levels and employment/unemployment rates in Canada. In overall, linear univariate models are quite adequate in terms of forecasting performance despite of their simplicity, whereas their multivariate generalization constitutes a natural extension to integrate the interrelationships between individual series with sufficiently good predictive power. The main criticism is that these modeling techniques rely heavily on the assumptions of parameter constancy and residual normality. Yet, these models are still appealing as long as evidence of shifts and/or non-normality is not strong enough to be successfully exploited by non-linear competitors (see Kunst, 2009, section 3.1, and Hendry and Juselius, 2001, section 3).

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[3] From a technical point of view, the strategy of combining multiple forecasts should offer performance gains from diversification. Similar to an asset portfolio, this forecasting methodology can be viewed as a way of overcoming the overall uncertainty and the risk factors surrounding the model specification/identification, and the dynamic characteristics of the underlying data series. Potentially, forecast errors of opposite signs will offset each other. Hence, composite forecasts are expected to minimize the magnitude of the aggregated forecast errors. The standard approach to combine forecasts involves the weighted average of individual forecasts. However, more complex weighting schemes such as linear regression have been proposed in the literature to exploit all possibilities of offsetting and minimizing forecast errors (see Timmermann, 2006).

As discussed above, properly designed non-linear models are empirically proven to produce excellent in-sample fit; their out-of-sample forecasting ability, however, largely depends on the predictability of future changes in regimes (see Bessec and Bouabdallah, 2005). Given that the primary objective of this study is forecasting, non-linear alternatives will not be explored because of their modeling complication and forecast uncertainty in the presence of unanticipated breaks. Instead, the potentially adverse effects of structural changes and near-integration will be tackled by a number of forecast combination strategies commonly used in the literature. The large variability in the data will be alleviated by the technique of logarithm transformation, which will be discussed in greater detail in section 5.3 below.

4. Methodology

This section analyzes various empirical issues and summarizes the approaches adopted to estimate and predict the EI claim levels over the available sample period from January 1997 to February 2011 for a total of 170 observations.

4.1. Forecasting Strategy

For forecasting purposes, out-of-sample predictions in this study will focus on two short-term horizons at one and six-months-ahead, and one medium-term horizon at twelve-months-ahead. The forecasting exercises start with the partition of the entire historical data into two segments. The first one is referred to as the specification subsample over which a given class of modelling will be set out and estimated. The second one is the prediction subsample over which predictions and their evaluations will be performed. There are no well established statistical procedures to determine the optimal subsample sizes. However, the existing choices seem somewhat related to the data availability, the forecasting horizons, and the data dynamics such as non-linearity, structural breaks, etc. It is worth mentioning that forecasters always face a trade-off between two opposing considerations that are widely discussed in the forecasting literature, namely, an unbiased estimate and a minimized forecast variance. In the presence of data heterogeneity, lengthening the specification subsample over different regimes implies the reduction in variance of forecast errors at the expense of more biased forecasts. Thus, setting up the estimation window size for an out-of-sample forecasting experiment is an art of balancing between "*using too much or too little data to estimate model parameters*" (see Clark and McCracken, 2009, p. 1).

With 16 years of monthly observations, Fauvel et al. (1999) employ a ten-year specification subsample, while Milas and Rothman (2007) set subsample sizes of 24 to 33 years out of a total of 38 to 47 years of quarterly data. Note that these two studies involve the prediction of labour market variables other than the EI claims, like the employment levels and the unemployment rates. Accordingly, I settle on a roughly 63%-37% split. The specification subsample span nine year of monthly data from January 1997 to December 2005 with 108 observations. The prediction subsample covers data from January 2006 to February 2011. This setup allows me to have 51, 57, and 62 observations to evaluate the performance of forecasts respectively at twelve, six, and one-month-ahead horizons.

The bias-variance trade-off motivates researchers' decisions on how to construct observation windows for estimations and forecasts. The most popular approach involves rolling windows often recommended for use to generate predictions if there is clear empirical evidence or strong theoretical belief in a growing evolution of the system through time. The observation windows may be of either fixed or variable length and essentially associated with a moving forecast origin. First of all, the model identification and estimation will be done over the initial specification subsample, which includes, for example, observations from periods T_0 (i.e. the initial forecast origin) to T_1. The computation of h-step-ahead forecasts will be carried out as of period $T_1 + h$. Next, the forecasting origin rolls ahead by one increment. The specification subsample will now span from periods$T_0 + 1$ to $T_1 + 1$ if the fixed-length method is employed. The h-step-ahead forecasts are then constructed at period $T_1 + 1 + h$. The entire procedure is repeated until the end of the prediction period is reached. Note that this methodology is different from a non-linear model, whose time-varying parameters are driven by state variables to switch across regimes (see Fauvel et al., 1999). Following the prevailing practices in recent macroeconomic literature,[4] the fixed-length rolling window procedure is employed as a way to account for structural changes that appear obvious from the visual inspection of the time series to be forecasted, EI claims (see section 1 of this paper).

[4] See Montgomery et al. (1998), Fauvel et al. (1999), Milas and Rothman (2007), and Choi and Varian (2009).

4.2. Model Specification

The linear $ARIMA\,(p,d,q)$ model will be used as the benchmark for estimating and forecasting the future demand for EI benefits. Next, a set of dynamically interrelated variables will be jointly employed in a $VARMA(p,q)$ system in reduced form to allow the possibility of feedback effects between them. For simplicity, I consider the VAR, which completely ignores the moving average parts in the innovations, as a special case of VARMA.[5] If cointegration among endogenous variables exists, the VEC modeling framework will be adopted.[6]

As discussed in section 3, parsimony in parameterization is particularly important for in-sample stability and out-of-sample forecasting in a multivariate setting. A large VAR/VEC system will typically lead to inefficient parameter estimates due to the two-fold complications of exponential parameter growth and reduction in degrees of freedom. On the other hand, a low dimensional VAR/VEC often generates unstable parameter estimates and poor future predictions as unexplained information will be shifted to the disturbance term. Therefore, several variables will be considered during the construction of these VAR/VEC models, but the dimension of the VAR system is restricted to four.[7] Choices of variables in this study are largely derived from the selection of Claus (2001) in the construction of a customized employment outlook named the Composite Index of Leading Indicators for Employment (LIE) on the ground that factors that affect the employment growth would potentially be important driving forces of demand for EI/UI benefits. Broadly, five categories of candidate variables will be under consideration:

1. **The primary series of interest**, namely, the series of Initial and Renewal Received Claims for EI (EIC).

2. **Aggregate domestic activity indicators**: The variables to be considered are GDP and the Canadian Composite Leading Indicator (CCLI) from Statistic Canada. The latter series is composed of ten different components in the economy that lead the domestic activities and broadly represent the GDP. These two variables may reflect the principal mechanisms that capture the business cycles. Indeed, the use of single

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[5] The identification of VARMA (p,q) processes is computationally difficult because the autocovariances and cross covariances between variables and their lags are in the form of matrices, which make it extremely complicated to trace the patterns across them (see Hakkio and Morris, 1984, p 10).

[6] In fact, a VEC is a restricted VAR in the sense that the cointegration relationships between endogenous variables are embedded into the model to impose convergence to their long-run steady-state while allowing temporary deviations and gradual adjustments in the short-run dynamics (see Emerson, 2011)

[7] Stock and Watson (2001) define a small VAR as one comprised of up to three variables.

composite indexes that combine information content from a large number of relevant indicators offers a convenient solution for dimension reduction in VAR modeling. For example, Brischetto and Voss (2000) produce forecasts of Australian economic activity using three different composite leading indicators through a set of bivariate VARs. Notice that the CCLI also incorporates the US composite leading indicator, which is highly influential for the trends in Canadian growth, jobs, and subsequently, EI claims, since the Canadian economy relies heavily on its exports to the US as its largest trading partner. It is worth mentioning that the UI initial claim series constitutes one of traditional leading indicators in the U.S. but it is not the case for Canada.

3. **Labour market indicators**: These include unemployment rates (UR) drawn from the Labour Force Survey (Statistics Canada) and the Net Employment Outlook (NEO) compiled from the Manpower Employment Outlook Survey conducted quarterly by the Manpower Group Inc., for which a representative sample of employers from different regions and industries are asked to indicate their anticipation of staffing over the next quarter. The NEO is derived as the difference between the percentage of respondents who anticipate a hiring increase and of those who plan to reduce the near-term level of their workforce. This forward-looking series has been empirically proven to have significant predictive power for employment trends and be a better indicator of future labour market conditions relative to the employment rate counterpart drawn from the Labour Force Survey (see Fauvel et al., 1999, p. 31). Another employment metric, such as the Google Job Search Index, has been empirically shown to have high predictive power on the UI claims in the US (see Choi and Varian, 2009) but it was developed very recently (since 2004).

4. **Financial and monetary indicators:** Monetary variables such as interest rates, exchange rates, and price indexes are expected to capture the impacts of monetary policies on the real economy, specifically, through the channels of production costs and exports. Selected variables for this study consist of the interest rate spread, the Fisher Commodity Price Index (FCPI), and the Canadian-dollar Effective Exchange Rate Index (CERI) from the Bank of Canada. The interest spread (IRS), also referred to as the yield curve, is widely used in the forecasting literature. It is defined as the difference between long-term and short-term interest rates; in particular, the difference between the ten-year-and-over Federal Government marketable bond yield and the three-month Treasury Bill rate.

The direction of the interest rate spread, or the shape of the yield curve, is driven by interest rate cycles, which are, in turn, mainly governed by changing expectations, business cycles, or monetary policies. Representing the opportunity cost of holding money, the interest rate spread has been used as a leading indicator of economic activity via its impact on consumers' spending/saving activities and producers' investment/hiring decisions. A positive spread, or a normal yield curve, generally predicts an expansionary period, which is characterized by strong consumer and business spending together with growing loan demand. On the contrary, a negative spread, or an inverted yield curve, generally foresees a period of contraction during which consumer and business spending declines along with low demand for liquidity (see Furfero, 2010). The FCPI is compiled using a chained Fisher price index derived from 24 commodities manufactured across Canada and exported all over the world. The CERI is derived from the weighted average of a set of exchange rates between Canadian dollar and the currencies of major trading countries based on their respective trading ratios in goods, services, and non-energy commodities. As Canada is a net exporter, fluctuations in either FCPI or CERI will have crucial impacts on the economy, hence, on employment and demand for EI benefits.

5. **Domestic demand-side indicators:** Demand-side indicators such as the consumer confidence index reflect consumers' view on the state of economy via their spending/saving activities as well as their intentions. The Consumer Confidence Index (CCI) is constructed by the Conference Board of Canada from a random sample of Canadian households to measure the level of their optimism with respect to the current and anticipated near-term economic conditions based on their estimation of actual and expected spending/saving plans as well as their short-term employment outlook. As such, the CCI can serve as an appropriate predictor of sale trend, employment growth in production sectors (see Torgundrud, 1999), and consequently, trend in EI claims.

Supply-side variables such as the Business Confidence Index (BCI) from the Conference Board of Canada, which convey useful information about capacity utilizations and investment intentions, should be trustworthy indicators of future economic trends. However, a preliminary analysis reveals that the BCI series are also near-integrated. The inclusion of more than one series close to unit root in the same system turn out to be problematic because of the increased risk of spurious regression and the high possibility of non-convergence during parameter estimation (see De Boef and Granato, 1997).

Finally, the potential predictive power of various EI/UI program parameters on the demand for EI benefits also needs to be explored. It has been well recognized in the labour economics literature that changes in EI/UI program generosity will decisively alter patterns of work force participation and unemployment spell duration. Doug (1995) conducts a thorough review of literature regarding the top determinants of structural unemployment in Canada, in which the effects of the EI program on unemployment are explored in great detail.[8] He finds some significant micro evidence on the linkage between the UI program and unemployment, but the magnitudes of estimates are small overall. On the contrary, macro-level studies report conflicting results due to the large extent of uncertainty involved in the formulation of reliable indicators for the UI generosity that can best capture the dynamic complexity of the program using time series. In addition, there is difficulty in isolating the pure effects of the UI program on aggregate unemployment because of the underlying feedback mechanism between them.

In fact, the construction of an accurate EI/UI index requires an in-depth knowledge of numerous program parameters, which are highly regional and individual specific, and complex computational frameworks.[9] After all, the EI system has long been known to concurrently exert two opposite effects on unemployment as behavioural responses vary greatly along both intensive margins (choices of employment/unemployment duration) and extensive margins (labour force participation decisions). Recall from the theory of rational expectations and optimization that individuals tend to choose their labour supply (participation vs. non-participation) or job search effort (unemployment vs. employment) in such a way as to maximize their utility over a certain time horizon. A more generous EI program with higher benefit rates, shorter minimum work requirement, and/or longer maximum benefit duration will raise the opportunity cost of job search and lower that of leisure. At the intensive margin, this situation will induce more unemployment among employed workers who exceed the minimum requirement. It will also postpone job search activities and lengthen the expected spell duration of those who are currently unemployed until they exhaust their benefit period. At the extensive

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[8] An updated version of this study is not available. Recent research on the potential effects of EI generosity on employment/unemployment involve micro-level rather than macro-level data.

[9] An EI/UI index of generosity should include the following components:

1. The program coverage;
2. The legislated replacement rate and the maximum benefit amount;
3. The entrance requirements such as minimum qualification period, waiting period and disqualification/disentitlement period;
4. The benefit duration such as maximum benefit period and extended benefit program;
5. The allowable earning provision.

See Doug (1995), Appendix 2 for a detailed discussion of the measurement of EI generosity.

margin, the propensity for participation among those with no prior labour force attachment will be higher, but the working weeks/days of those who previously worked less or more than currently required will respectively increase or decrease. Briefly, individuals will adjust their work or job search decisions in response to the degree of generosity of the EI/UI program so that there is an apparent peak in the distribution of choices in the vicinity of both intensive and extensive margins (see Benjamin et al., 2007, chapter 18).

Since the EI program may generate both incentives and disincentives, its net effect on the labour supply is hence ambiguous. As an attempt to empirically verify these points, a preliminary analysis of the relationship between EI claims and the Fortin index for Ontario and Quebec suggests that they do not Granger-cause each other.[10] In fact, the Fortin Index, provided by Prof. Pierre Fortin from Université du Québec à Montreal, is defined as the ratio of potential total benefit entitlements with respect to the minimum labour income required for benefit eligibility (see Arnau et al., 2005), thus, appears more suitable for the generosity of EI Regular Benefits. Nevertheless, Statistics Canada does not provide any break-down by types of benefits for its measure of EI claims. As such, the Fortin Index will be unable to capture the full effects of the EI program with respect to special benefits. In addition, this forecasting experiment is also carried out at the national level for which the aggregate Fortin index is not useful. Further improvement to the Fortin index by breaking the data into EI administrative regions is not feasible due to budget constraints in data acquisition.

As such, after initial explorations for the set of potentially relevant predictors of the EI claims, two candidate variables, the BIC and the Fortin index, are excluded. A total of 50 VAR/VEC models are selected for the purpose of estimation, prediction, and particularly, combination of forecasts (see Table 1).

4.3. Model Identification

Tests for presence of unit roots are applied to each individual series over the entire period examined in order to determine the appropriate order of integration. Tests for cointegration between endogenous variables are also performed on each VAR specification over the whole sample period. Cointegrated systems are estimated using VEC modeling; otherwise, non-stationary variables will enter the VAR in appropriately differenced form.

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[10] This implies the historical values of one variable do not help to predict the future movements in the other.

As estimation and forecasting results are sensitive to the choice of lag orders, the parameters of an ARIMA and the order of a VAR/VEC will be determined on the basis of minimizing an objective information criterion (IC) over the specification period. ICs have gained great popularity in the forecasting literature because of their ability to reconcile the two-choice dilemma in the time series modeling, namely, the "*curse of dimensionality*" and the correct model specification, by combining goodness-of-fit (i.e. minimizing the residual sum of squares) with parsimony (i.e. penalizing excess parameters) (see Meyler et al., 1998, p. 18-20). Among the three typical ICs, the Akaike information criterion (AIC) is asymptotically efficient but not consistent, while the Hannan-Quinn criterion (HQ) is asymptotically consistent, and the Schwarz Criterion (SC) is strongly asymptotically consistent but not efficient (see Mantalos et al., 2008, p. 62-64). As an efficient model selection criterion, the AIC helps to achieve higher predictive performance in both small and large samples. However, it often leads to biased fit, which becomes particularly severe in finite samples because it has a tendency to overestimate the lag order relative to that of the true model. This finding again highlights the fundamental trade-off between in-sample goodness-of-fit and out-of-sample forecasting ability (See Lutkepohl, 2005, section 4.3). Hurvich and Tsai (1988) introduce a new class of bias-corrected AIC, the AICc, which has an extra penalty term as a function of the sample size and the lag orders chosen by the original criterion. They demonstrate via theoretical proofs and simulation results that the AICc is not only asymptotically efficient but also consistent, and its bias reduction in small samples is substantial compared to the original AIC. As such, model selection in this study is based on the AICc for in-sample estimations and on the AIC for out-of-sample forecasts.

4.4. Forecast Combination

As a final step in the development of an adequate forecasting methodology, individual point predictions from selected ARIMA/VAR/VEC alternatives will be pooled together to produce aggregate forecasts that are empirically proven to be robust to structural changes, and near-integration. The following weighting schemes will be considered. The first one is the simple equal-weight average (MEAN). The second one is the simple median (MEDIAN). The third one is the "*Most Recent Best*" (MRBEST) from Stock and Watson (2004), which places the full weight on the individual forecast having the best historical predictive performance as being estimated by the average MSE over the last four periods. The fourth one is the "*Focus Forecasting*" (FOCUS) from Ringuest and Tang (1987), which selects the point forecast with minimum anticipated loss reflected in the absolute error during the immediate preceding period. The underlying argument for these two schemes is that the model that achieved the highest performance record in the past is expected to be the champion in the current period. The fifth scheme is the "*Discounted Mean Square Forecast Error Forecasts*" (DMSE) from Stock and Watson (2004) that applies a weighted average, where the weights are inversely proportional to the historical error losses of each component forecasts. Past forecasting accuracy as being measured by the MSE is further time-discounted with a discount factor less than unity in order to attach greater influence to recent error losses[11].

More complex combination procedures involving linear regressions, which require a further partitioning of the predictive subsample into two: one for estimating the weights, and the other for evaluating the forecast results, are not implemented, given the limited data availability.

4.5. Forecast Evaluation

Forecasting models in this study will be assessed for their predictive performance on the basis of widely used criteria in the literature.

4.5.1. Forecasting Accuracy

The most widely reported indicators/tests of how accurately a model predicts future values of a time series are:

1. **Statistical Measurements of Forecast Error Loss:** These include the three most popular error metrics, the Root Mean Square Error (RMSE), the Mean Absolute Error (MAE), and the U-Theil Coefficient. The RMSE measures the square root of forecast error variance, or in other words, the standard deviation of forecast errors (see Kunst, 2009, section 7.1). The MAE measures the average magnitude in absolute terms of forecast errors over the prediction subsample. Both RMSE and MAE are also referred to as loss functions that are constructed on the concept of losses incurred by forecast errors. The optimal decision rule is to minimize the expected loss of forecast errors, i.e., lower values mean better predictions (see Kunst, 2009, section 7.2). The U-Theil Coefficient is an index of inequality that evaluates the degree to which forecasts from a particular model differ from those produced by a primitive benchmark, typically, the random walk, or "no change" model. It is in fact equal to the ratio of the RMSE of the former to that of the

[11] The time discount factor in this study is set to 0.9 as suggested by Stock and Watson (2004).

latter. Smaller U-Theil scores imply better performance, and those under unity in value indicate forecasting improvement with respect to the random walk alternative (see Kunst, 2009, section 7.4).

The RMSE is often criticized in the literature for being sensitive to the units of measurement and the presence of outliers as it squares the errors prior taking the average. In addition, it ignores the serial correlation between forecast errors, and the quadratic loss function it represents may not reflect the true error costs. The MAE is less vulnerable to influential observations, hence, more robust in the face of error variability. The U-Theil is able to take into account error autocorrelations but still retains the undesirable property of strong sensitivity to outliers (see Kunst, 2009, section 7.1, 7.2, 7.4; Barceló and Casas, 2002, p 12-14).

2. **Hypothesis Testing:** These tests allow us to conclude if the difference in the forecasting performance of two competing models as measured by an error loss function is statistically significant. The two most commonly reported are the Diebold-Mariano (DM) tests of equal forecast accuracy and the Harvey, Leybourne and Newbold (HLN) tests of encompassing forecasts. The DM tests evaluate the predictive abilities by focusing on the significance in the difference of loss due to forecast errors between two competing models. Harvey et al. (1997) find that DM tests also suffer from increasing "*oversizing*", as the forecast horizon grows larger.[12] To mitigate this shortcoming, they suggest an adjustment to the original test statistic by a correction factor as a function of both sample size and forecast horizon.[13] The HLN tests are based on the same predictive accuracy criteria as established by Diebold-Mariano and are particularly useful in determining the subset of forecasts to be pooled into an aggregate forecast.

   Busetti et al. (2009) observe through an extensive Monte Carlo investigation an overall greater power of the HLN tests relative to the DM counterparts in the sense that the latter frequently fails to reject the null hypothesis of equal forecast error loss, whereas the former indicates a potential forecasting gain from using the alternative model. However, according to Harvey et al. (1998), the HLN tests are prone to type I errors with unacceptably high rejection frequencies of a true null hypothesis when the distribution of forecast errors is non-normal.

[12] The DM tests tend to reject the null hypothesis more often at large forecast horizons (see Harvey et al., 1997)

[13] Harvey et al. (1997) demonstrate through Monte Carlo simulations that this modification substantially improves the power of the test in finite samples.

4.5.2. Direction of Change

The purpose of this evaluation criterion is to assess the ability of a model to accurately predict the direction of changes in a series without regard to their magnitudes. Cawthray et al. (2001) construct the "*Confidence Index*" (CI) as the fraction of correct directional forecasts. Talwar and Chambers (1993) investigate the "*Directional Accuracy*" (DA) of forecasts proposed by Cicarelli in 1982. This metric measures the probability of correctly predicting the direction of change as the sum of the probability of precisely identifying an actual increase and the probability of precisely identifying an actual decrease.

4.5.3. Retained Approaches

Forecasting models with low RMSE/MAE/U-Theil but also low CI/DA are implausible. In addition, it is important to know if differences in forecasting accuracy are statistically significant. Given that each forecasting evaluation method has its own limitation, I opt for a wide range of diagnostic tools for the quality of forecasts including the RMSE, the MAE, the U-Theil index, the CI, the DA, and statistical assessments such as the modified DM tests and the HLN tests.

5. Data

5.1. Description

The majority of time series data used in this study are obtained via CANSIM. Financial and monetary variables such as interest rates, the commodity price index, and effective exchange rate index are also posted at the Bank of Canada's official website.[14] The EIC are originally compiled from HRSDC's administrative data and then released by Statistics Canada. An Initial claim corresponds to the application for EI benefits that was first approved in the last 52 weeks. If the EI benefit period established by an initial claim has become inactive for more than four weeks due to various reasons, the filing of another claim within this 52-week time frame will reactivate that temporarily interrupted benefit period and is referred to as a renewal claim. The CCLI is the simple unweighted average of ten individual indicators representing the major components of national GDP: the average work week, housing index, US composite leading indicator, money supply, new orders of durable

[14] Various rates and statistics from the Bank of Canada are available for public use at http://www.bankofcanada.ca/en/rates/index.html

goods, retail trade of furniture and appliance, sales of durable goods excluding furniture and appliance, shipment to inventory ratio of finished products, stock price index, and business and personal services employment. The NEO is provided by the Manpower Group Inc. The CCI is obtained from the Conference Board of Canada. Most of data are of monthly frequency, except the NEO and the CCI, which are released on a quarterly basis. The monthly series of CCI has been available only recently (since 2002). The selected variables are often published as both seasonally adjusted and unadjusted. A few exceptions are the three-month Treasury Bill rate, the ten-year-and-over Federal Government marketable bond yield, and the CERI, for which deseasonalization is not applicable. The CCLI is constructed as smoothed and unsmoothed. The FCPI and the CCI are left unadjusted. The elimination of seasonal noise is performed through the recent X-12-ARIMA procedure from the US Census Bureau. The CCLI is smoothed by means of five-month moving averages to remove excessive irregularities due to business cycles and data revisions. Table 2 provides a detailed description of the data sources as well as their availability.

As mentioned in the previous section, the full sample period is chosen to extend from January, 1997 to February, 2011, where all variables under consideration are published. Beside the EI Initial and Renewal received claims (EIC), a set of eight other macroeconomic series are selected to enter into 50 different VAR/VEC specifications as endogenous variables: the CCLI, the chained GDP at basic prices, the UR, the NEO, the FCPI, the IRS, the CERI, and the CCI. There is no distinction between dependent and independent variables in a reduced form VAR/VEC context because this methodology presumably relies on the assumption of mutual interaction between them. Note that the measurement of GDP is currently expressed at basic prices and market prices. GDP at basic prices equals the historical measure of GDP at factor cost plus the net tax on factors of production, while GDP at market price corresponds to the GDP at factor cost plus the net tax on both factors of production and products. The decision to use GDP at basic prices in this study is primarily based on the rationale that this measure better represents production costs, and thus, more directly affects hiring activities. GDP at market prices reflects actual consumption expenditures, hence, also has an important impact on the economy through changes in consumption patterns (see Lal, 2003). However, this series is available only in nominal dollars and on a quarterly basis. GDP at basic prices is produced monthly and converted into real terms by means of both a weighted index and a chained volume index by Statistics Canada. Data at the provincial level are provided for the EIC and the UR. Regional data on NEO and the monthly CCI have been published since 2002.[15] However, the regional CCI series are not used in this study because they are not included in HRSDC's subscription with Conference Board of Canada. Analysis at the provincial level will be carried out solely for the two largest provinces: Quebec and Ontario.

5.2. Treatment of Seasonality

Following common practices in the literature, the forecasting exercises in this study are undertaken using seasonally adjusted data provided by Statistics Canada. In fact, there are two rationales supporting this choice. First of all, most of the critiques regarding the inadequacy of seasonal auto-filtering procedures are related to the old version of seasonal adjustment from the US Census Bureau, X11-ARIMA. The newer version, X12-ARIMA, offers much greater flexibility and customization in the sense that it "*permits user-defined regression for unusual or nonstandard calendar effects and includes a variant of the TRAMO algorithm*" (STATCAN, 2009, p. 64). Secondly, intensive forecasting exercises using both seasonally adjusted and unadjusted data from Bell and Sotiris (2010) show strong statistical evidence that the X12-ARIMA seasonal adjustment program is not only undetrimental in most instances, but also beneficial to the forecasting accuracy in some cases. All the Statistics Canada seasonally adjusted series have been revised historically on a regular basis using the most updated seasonal adjustment process.

5.3. Transformation

The unadjusted indexes such as FCPI, CCI, CERI, and IRS are smoothed by five-month averages to alleviate erratic movements due to business cycles which may adversely interfere with the underlying estimation assumptions.[16] The regional NEOs, starting since 2002, are merged with the historical national NEO from January 1997 to December 2001 to obtain a full length history. The three quarterly NEOs are then converted to monthly by the method of cubic spline interpolation (see Fauvel et al., 1999, section 3). Similarly, the monthly CCI, available only after the end of 2001, is combined with its quarterly series. Missing months are also filled by cubic spline interpolation.

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[15] Manpower Group Inc. offers four regional NEOs (Atlantic, Ontario, Quebec and Western Canada), whereas Conference Board of Canada provides five regional CCIs (Atlantic, Ontario, Quebec, British Columbia, and Prairies).

[16] The choice of a five-month window for the moving averages is somewhat arbitrary. The main rationale is to be consistent with the smoothing procedure for the CCLI by Statistics Canada.

All variables are expressed in natural logarithms. Log transformation, which has become standard in financial and economic time series analysis, is intensively applied in the literature for three-fold reasons. First, it allows the multiplicative relationship between variables and the exponential trend of individual series to be respectively expressed in additive and linear form. Second, it has the effect of normalizing the data, and thus, is regarded as a way to reduce the inefficiency in statistical inferences induced by non-normality and heteroskedasticity, which often exist in level time series. Third, it facilitates the interpretation of parameter estimates in terms of percentage changes rather than unit changes (see Tsay, 2010, chapter 2). However, this type of transformation can be applied exclusively on strictly positive data. To circumvent this shortcoming, a constant may be added to the series with negative data points prior to taking the logarithm (see Tsay, 2010, chapter 2). It is worth recalling that the IRS is computed as the difference between the ten-year-and-over Federal Government marketable bond yields and the three-month Treasury Bill rates, and the NEO is calculated as the difference between employer respondents with rise and fall in staffing intentions. This manipulation inevitably yields some negative values for which it is impossible to take the logarithm. Following the common practice in the literature, both the IRS and the NEO are incremented by 100 before applying the log transformation.

6. Results

This section reports the estimation and forecasting results. For the sake of exposition, figures are presented exclusively in Appendix A and tables in Appendix B at the end of this paper.

6.1. Unit Root Tests

All log transformed data are tested for the existence of unit roots over the full sample period from January, 1997 to February, 2011. All variables will be tested in levels. Integrated series will also be tested in first difference forms. The process of testing for unit roots usually starts with a visual inspection of the plots of sample autocorrelation functions (SACF) and sample inverse autocorrelation functions (SIACF). Figure 2 depicts the correlograms of four selected series, GDP and the three log EIC across national and provincial levels. In fact, the SACF is useful for spotting the evidence of integration, while SIACF helps to detect sign of over-differencing. The SACFs of all level data decay very slowly; hence, they clearly reveal evidence of non-stationary or high persistent near-non-stationary characteristics. On the contrary, all the SACFs of their first difference die down quickly and the SIACFs do not reveal a typical dampening pattern induced by over-differencing (see SAS, 2010, chapter 7).

Statistical testing results are presented in Table 3. Since seasonal patterns are not observed in the correlograms of any time series including the unadjusted ones, the unit root tests will be conducted using the Augmented Dickey-Fuller (ADF) and the Elliot, Rothenberg and Stock (ERS) techniques. The popular ADF tests are asymptotically efficient but subjected to substantial size distortion and have particularly low statistical power with respect to highly persistent stationary processes in the sense that they fail to accurately discern the marginal difference between integration and near-integration. The power of the test deteriorates even further with the inclusion of a constant or a trend into the test equation. To address this shortcoming, Elliot, Rothenberg and Stock (ERS) derived in 1996 a class of efficient unit root tests, which are much more powerful, especially when the series in question contain a near-unit-root.[17] The lag order of the test regression is selected on the basis of a modified information criterion, more specifically, the modified AIC (MAIC), as recommended by Ng and Perron (2001). According to these authors, the MAIC has higher ability than the traditional counterparts like the AIC or the SIC to determining the optimal lag length for the unit root test equation, notably in the presence of long serial dependency in the innovations (See Zivot and Wang, 2005, chapter 4).

Table 3 presents two main set of results. Columns 3 through 11 display the hypothesis tests for unit roots with three specifications: none or no constant (columns 3-5), constant (columns 6-8) and trend (columns 9-11). Columns 12 through 15 report the τ-statistics for the ADF tests or the p-statistics for the ERS tests and the associated p-values for the coefficient estimates of the constant and the trend. As ERS tests are more robust to sample size and near-integration, my conclusions will be typically based on their indication. In the case of conflicting results among the three specifications, the test statistics from the coefficient estimations and the graphs of series in question will be consulted to make assumptions about the underlying specification from which the answer from the respective ERS unit root test will be retained.

[17] See Zivot and Wang (2005), chapter 4.6 for detailed discussion of the test procedure.

Results from the two types of unit root tests over all testing specifications yield unanimous conclusions with respect to the non-stationarity of all variables of concern, except for the three log EIC series for which the test outcomes are highly ambiguous. Not only do the τ-statistics and the corresponding p-statistics of the two tests disagree, but the significance of the same test also varies across different specifications. As mentioned above, the decision in these cases will rely on the ERS tests of the specification with significant coefficient estimates. There is strong statistical evidence supporting the existence of a linear trend in the log EIC in Ontario, which is also confirmed by the visual check on the plot of the time series (see Figure 6). The corresponding ERS test is unable to reject the null hypothesis of unit root. On the contrary, only constant estimates are significant for the log EIC in Quebec and Canada, and the corresponding ERS tests respectively reject the null at the 5% level. Thus, I conclude that only the log EIC in Canada and in Quebec follow stationary processes. All other log-level series are integrated.

Given that no sign of non-stationarity appears in the SACF plots, the unit root tests in first differences are carried out uniquely by the ADF variant, which consistently rejects the null at least at the 10% level of significance, except for the none and trend specification of the log-first-difference CCLI (see Table 4). Yet, the trend coefficient in the test equation of this series is not statistically significant, while the constant estimate is. Thus, the conclusion will be drawn from the τ-statistics of the constant specification, which strongly support the evidence of stationarity of the log-first-difference CCLI at the 5% level. In summary, the ADF tests indicate that all integrated processes are stationary in first differences. In other words, their log-levels are integrated of order one.

It is interesting to notice that lag orders chosen by the MAIC for the unit root tests of the three national and regional log-level series of the respective EIC, NEO and UR are quite similar. Nevertheless, in case of the log-first-difference URs, the lag length selections vary dramatically across national and regional levels. Ng and Perron (2001) observe from repeated simulations that the majority of unit root tests suffer from severe power loss when the sample size is finite and the underlying data generating process (DGP) exhibits near-non-invertibility, notably with large negative moving average components. In such situations, the choice of lag order suggested by the standard AIC and BIC criterions is too short to adequately capture the long serial dependence in the data. To provide proper size adjustment to unit root tests, Ng and Perron propose a correction to the "*lag truncation*" issue by adding an extra penalty to the underidenfication,[18] particularly in the presence of fairly large negative serial correlation in the residual of the DGP. This new family of information criteria is also referred to as the Modified Information Criteria (MIC). They present proofs regarding the asymptotic properties and Monte Carlo evidence to the substantially enhanced robustness of the MIC, more specifically the MAIC, against size degradation and power deterioration in small samples.

In regards to the unit root tests of the log-first-difference URs, the traditional AIC would choose a zero lag length in all three national and regional cases, while the MAIC correspondingly select a lag order of four, zero, and eight for all three specifications in Canada, Quebec and Ontario. As such, the MAIC imposes additional penalties to the log-first-difference URs in Canada and Ontario. On one hand, we know from the mathematical construction of the MAIC that this penalty is intended to prevent underfitting of the test autoregression in the occurrence of large negative moving average roots. On the other hand, statistical evidence demonstrates that such a modification to the original AIC would yield, on average, a significant power gain for unit root tests. In practice, whether or not the actual error process of the respective log-first-difference UR in Canada and Ontario does contain a significant negative serial correlation, we are unable to determine with certainty because the true form of a DGP and its lag order is unknown a priori. Yet, a visual examination of the plots of the log-first-difference URs from Figure 3 show that although they all appear to follow zero mean stationary processes,[19] there are apparent irregularities in the Canada and the Ontario data, while the Quebec series oscillates quite evenly around its long-run average. The Canada series records a sharp spike near the end of 2008 followed by a sudden drop in early 2009. The Ontario series exhibits asymmetric fluctuations, with extreme data points concentrating more often above the zero mean. These characteristics, which have been identified in the literature as a highly possible cause of large negative moving average roots (see Ng and Perron, 2001, p. 1519-1520), might be helpful in explaining the obvious discrepancy in the lag order determination by the MAIC across national and regional log URs in first difference.

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[18] This penalty term is a function of the first lag in level, its coefficient estimate and the residual variance in the test regression. The ADF test is in fact the t-test on the parameter estimation for the first lag in level (see Ng and Perron, 2001, p 1521-1523). Note that the conventional ICs uniquely penalize the case of overspecification.

[19] Constant and trend estimates are not statistically significant for the three log-first-difference URs (see Table 3).

6.2. Cointegration Tests

All of the 50 VAR specifications will be tested for the existence of cointegration using Johansen's likelihood-based system cointegration testing over the entire sample. However, due to the complication involved in the analysis of lengthy results, particularly when near-integration and possibly, negative moving average exist in the dataset, cointegration tests will be later presented in the next section for the selected VAR models, which display adequate in-sample properties across the three investigated geographical entities.

6.3. In-sample Analysis

An objective criterion, the AICc, and various residual diagnostic tools are used jointly to identify the appropriate lag orders and assess the model suitability over the entire sample period (i.e. from January 1997 to February 2011).

6.3.1. ARIMA Models

The model selection procedure on the basis of the AICc, with the maximum lag length set to 12,[20] specifies the candidate models, $ARIMA\,(2,0,11)$, $ARIMA\,(1,0,11)$, and $ARIMA\,(4,1,4)$, respectively, for the log EIC in Canada, Quebec and Ontario. Note that the Box-Jenkins method for ARIMA identification, which relies primarily on the visual inspection of the SACFs and the sample partial autocorrelation functions (SPACFs), is not utilized because of the high subjectivity in graphical interpretations (see Ozaki, 1977, p 297-299).

Panel A in Table 5 provides a statistical summary of the adequacy of a given model based on hypothesis testing of whether its residuals resemble white noise. The chosen lag orders and the associated AICc(s) are correspondingly displayed in columns 2 and 3. The 12-lag Breusch-Godfrey (BG(12)) tests for serial correlation, the Jarque-Bera normality tests (JB), the three-dimension Brock, Dechert, Scheinkman and LeBaron (BDS(3)) tests for non-linear serial independence,[21] and the White (WHITE) tests for

[20] The choice of maximum lag length is somewhat arbitrary depending on data availability. The lag length should be sufficiently large to account for serial dependence in the data but should leave enough observations for adequate parameter estimations.

[21] The BDS statistics check against any departure from time-based independence. The BDS tests are useful to uncover any non-linear dependence in a linear modeling context and vice versa (see EVIEWS, 2009, p 411-414). The dimension of the test is set to 3 following the recommendation of Diks (2010), p 20.

heteroskedasticity[22] are respectively reported from columns 5 to 8. The standard error of the fitted residuals (i.e. the RMSE) and the decomposition of the error variance (i.e. the MSE) into the bias proportion (BIASP), variance proportion (VARP) and covariance proportion (COVP) are presented in columns 9 to 12.[23] Recall that a good fitted/forecasted series should have the bias and the variance proportion as small as possible so that the most part of errors would concentrate in the covariance proportion (see Fauvel et al., 1999, p. 121-122). As we can see in this table, there is enough statistical evidence to support the independently and identically distributed (i.i.d.) properties of the residuals from these three models because the associated p-values of all test statistics are consistently above the 10% level.

Next, we examine the ARMA structures of the three selected models, $ARIMA\ (2,0,11)$, $ARIMA\ (1,0,11)$, and $ARIMA\ (4,1,4)$. The inverted roots of the AR/MA polynomials are listed in the column 1, 3, and 5 in Panel A of Table 6, where the AR modulus is shown in the upper subpanel, and the corresponding MA modulus in the lower subpanel. Apparently, these models satisfy the stability condition of stationarity and invertibility, with all inverted AR and MA roots lying strictly inside the unit circle. However, Canada and Quebec models possess a large number of MA parameters close to unity, and the Ontario counterpart contains near unit roots in both AR and MA components. The near-integration of the Ontario estimated process is obviously revealed through the dampening and gradually attenuated nature of impulse responses of the log EIC to one-time shocks in its innovations.[24] The responses from the Canada and Quebec models also vanish slowly but more quickly relative to the former (see the top panel of Figure 4).

Near-non-invertibility, particularly negative MA near unit roots, has emerged as a problematic econometric issue because of its detrimental effects on the conventional statistical inferences such as hypothesis testing and confidence intervals (see Ng and Perron, 2001; Hjalmarsson and Österholm, 2007). As such, it is important to provide some insights into the potential underlying causes of the problem. Specifically, large negative serial dependence may be induced by extreme observations such as outliers or structural breaks in

[22] There is no established rule regarding the appropriate lag length to the BG test equations. In general, enough lags should be included to account for any serial correlation effects at longer lags. It is usually suggested to set the number of lags to 12 or 4, respectively, to monthly or quarterly data because autocorrelations between errors are supposed to occur within one-year cycles (see Brooks, 2008, p 148-149).

[23] The bias proportion measures how far the mean of the fitted/forecasted values is from that of the actual data. The variance proportion indicates how different the variability of the fitted/forecasted values is from that of the actual data. The covariance proportion captures the remainder of any unsystematic errors (see Fauvel et al., 1999, p. 121-122).

[24] This characteristic of the impulse function from a near non-stationary process has been identified in Ozaki, 1977, p 297-299.

the series mean level and/or in the innovation variance (see Tsay, 1988). Other likely factors include over-differencing a series (see Plosser et al., 1977) or modeling a fractionally integrated process using ARIMA approximation (see Sowell, 1992).

Before engaging in further diagnostic testing of model stability, let us start with the graphical investigation of the actual vs. fitted logged series (see the top panel of Figure 5).[25] Note that the log EIC in Ontario enters the ARIMA regression in first differenced form. This is probably why several properties of its estimated ARIMA process such as lag orders and impulse functions, are quite different from the ones in the Canada and Quebec. We notice that the three logged EIC exhibit frequent excessive irregularities, with sharp peaks alternated by sudden drops. In spite of that, the fitted lines follow well the overall curvature of their respective actual data. In addition, the standardized residual plots (not presented here) do not show any specific pattern of non-normality or non-linearity that may rule out the whiteness of the innovation. Although we can spot some departures from the 95% confidence bands (i.e. +/- 2 of standard error (SE)), which imply the existence of influential outliers, they are not worrisome in my judgment because they are bounded in the vicinity of +/-3 SE. The removal of these observations by dummy variables potentially gives rise to other estimation problems due to diminishing in degrees of freedom.

As depicted in the top panel of Figure 5, the Canada series is characterized by a distinctively high record in early 2009, which might be explained by the conjunction of widespread economic recession since 2008 and temporary extensions of EI benefits from the EAP during the 2009-2010 and 2010-2011 fiscal years (see sections 1 and 2 of this paper). The demand for EI benefits gradually declined toward mid 2010 as the EAP's temporary employment stimulus measures came into play and slightly rise again in early 2011. The Ontario and Quebec logged EICs follow a similar path. Yet, the 2009 peak is less pronounced in Ontario. In Quebec, it is completely surpassed by two slightly higher records in mid 2001 and early 2003. Indeed, relative to Canada and Ontario, the Quebec log EIC displays a steady fluctuation pattern, which spreads more evenly around a constant mean.[26] This finding seems consistent with the stylized fact from CIRANO (2009) that Quebec has been known for a long time to have persistently higher unemployment rates than Ontario and Canada, but

[25] Standardized Residuals is the normalization of the regression residuals by its standard deviation (see EVIEWS, 2009, p 18). The actual and fitted series are in log-level. The regression residuals are in log-level for Canada, Quebec and in log-first-difference for Ontario.

[26] The constant estimate in the unit root test for log EIC in Quebec is strongly significant at 1% (see Table 3).

these historically large gaps have been shrinking steadily and negatively diverged for the first time in mid 2009. In other words, the economic convergence phenomenon has positively contributed to the dampening of the upward trend in demand for EI benefits during the recent global downturn. On the contrary, Quebec experiences the highest degree of variability in the EI claim volume, which manifests itself through a variance proportion of the largest magnitude when fitted by the $ARIMA\,(1,0,11)$ (see Panel A of Table 5 and section 1 of this paper).

Panel A of Table 7 lists the estimated dates for major breaks in parameter estimates with the corresponding F statistics and p-values from the Chow forecast tests[27] on the $ARIMA\,(2,0,11)$ (columns 2 to 4), the $ARIMA\,(1,0,11)$ (columns 6 to 8), and the $ARIMA\,(4,1,4)$ (columns 10 to 12). These results reveal sound evidence (at the 5% level of significance) for the presence of one breakpoint in Quebec (June 2005), two in Canada (July 2005; October 2008) and two in Ontario (November 2001; May 2008).[28] As expected from the analysis in the preceding paragraph, an important structural change occurs within the post 2008 period in the estimated DGP of log EIC in Canada and Ontario, but not in Quebec. Theoretically, the ideal way to cope with the structural instability should be to build two separate models with different parameter estimates and/or different specification classes over the pre-/post-break periods. Nevertheless, this technique is not feasible in time series due to the prevailing data shortage. The simplest and easy-to-implement remedy would be the inclusion of dummy variables for the breakpoints, which also make the AICc values change. The new set of choices are the $ARIMA\,(3,0,11)$ for Canada, the $ARIMA\,(2,0,11)$ for Quebec, and the $ARIMA\,(5,1,6)$ for Ontario. Residual checks are presented in Panel B of Table 5, while plots of actual vs. fitted are shown in the bottom panel of Figure 5.

The first remark is that the introduction of dummies leads to the selection of longer lag length for AR parameters of Canada and Quebec and for both AR and MA parameters of Ontario. A slight enhancement in goodness-of-fit in terms of AICc(s) and RMSEs is achieved at the expense of some other fit statistics. The influence of outliers is deflated as the residuals from Canada and Quebec models become now strictly bounded inside the +/- 3 SE bands. However, the JB test rejects the null hypothesis of normality at the 10%

[27] The conventional Chow tests fit the regression in question separately over two subsamples before and after the break date to determine whether there are significant shifts in parameter estimates. The Chow forecast tests compare the difference in parameter estimation over the entire sample and the longer pre-break period. The latter approach is considered as a helpful solution to the data scarcity problem in case of short post-break period (see EVIEWS, 2009, p 170;174).

[28] The choices of break points are based on the combination of sequence of Chow tests and the visual inspection of the series plots.

level for Canada. A quick glance at the impulse response functions in the bottom panel of Figure 4 and the ARMA structures from columns 2, 4, 6 in Panel A of Table 6 reveals a greater instability of these models relative to their counterparts without dummies. The inverted MA roots for Quebec and Ontario get closer to unit roots. A large inverted AR root is present in the estimated DGP for Canada, which is reflected in a much slower convergence of the impulse responses. Thus, the use of intervention dummies does not make any perceptible enhancement to the goodness-of-fit.

There are four possible reasons for this failure. First, as a statistics-based criterion, the AICc is subject to errors and noise. Second, the Chow forecast tests may be inadequate to accurately determine the date or detect the occurrence of some breakpoints, notably when they occur relatively close to each other or emerge gradually through the channel of innovations (see Cai, 2009, chapter 4). Third, in the latter case, the shock affects the mean level rather indirectly via its propagation to the whole ARMA structure (see Nielsen, 2004). An intercept dummy is not sufficient to capture the full impact of an innovative shift.[29] Fourth, the log EIC series are probably fractionally integrated with significant serial dependency over long horizons (see section 3 of this paper). This argument may be supported by the ARMA frequency spectrum plots (not presented here), which reach a sharp peak in Canada and Quebec (i.e. sign of under-differencing) and collapse to zero in Ontario (i.e. sign of over-differencing) at frequency zero (see Zivot and Wang, 2005, chapter 8).[30] More specifically, the SACF of the Ontario log EIC displays a hyperbolic decay pattern that typically characterizes the long and persistent memory of a fractionally integrated process (see Figure 2).[31]

In summary, the three log EIC series strongly suffer from the presence of large variability and structural changes, which are the likely cause of large MA components in the data. They also follow near-integrated and/or possibly (but not necessarily) long-memory processes.[32] Even though the selected ARIMA models (without or with intervention dummies) fit the data generally well, they are subject to high instability in parameter estimates. However, whether each of them might be better modeled by a non-linear specification,

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[29] The built-in ARIMA procedure in EVIEWS does not offer the flexibility to include an interactive dummy to the AR/MA terms.

[30] The spectral density of integrated processes asymptotes toward infinity in the neighborhood of frequency zero (see Zivot and Wang, 2005, chapter 8).

[31] The ACF of a stationary/fractionally integrated/integrated process respectively decays at geometrical/hyperbolic/linear rate (see Zivot and Wang, 2005, chapter 3).

[32] Short-memory processes subject to structural shifts may share very similar behaviours that are hard to be distinguished with long-memory ones (see Bisaglia and Gerlimentto, 2005).

the FARIMA framework, or the combination of both (see section 3 of this paper), is beyond of the scope of this study.

6.3.2. VAR/VEC Models

It is worth recalling that "*derivations of the VAR from a general DGP rely heavily on multivariate normality*", "*parameter constancy*", "*and statistical inference is only valid to the extent that the assumptions of the underlying model are correct*" (see Hendry and Juselius, 2001, p. 6-7). Nevertheless, the assumptions of normality, serial independence, and homoskedasticity are violated with non-negligible probabilities in the majority of 50 VAR specifications, which are also exposed to significant structural shocks, excessive fluctuations as shown in the previous section. Hendry and Juselius (2001, chapter 3) suggest some modifications to make a VAR "well-behaved", among which are lengthening the lag order, enlarging the information set with new variables, or using dummies for breakpoints. Yet, the first two solutions are not always feasible because of "the curse of dimensionality" mentioned in section 3.

Overall, the 13th specification, which is made up of the information set $\{EIC, GDP, FCPI, UR\}$, appears to have adequate goodness-of-fit properties across the three geographical entities of concern. The first tentative model identification, where the lag length is restricted to a maximum of six,[33] leads to the choice of unrestricted $VAR(5)$ for Canada, $VAR(4)$ for Quebec, and $VAR(4)$ for Ontario on the basis of both the objective AICc criterion and the lag exclusion tests. Panel B of Table 7 presents the list of breakpoints estimated by the Chow forecast tests. The VAR systems are then reestimated with the inclusion of breakpoint dummies. The new set consists of $VAR(6)$, $VAR(5)$, and $VAR(4)$ for Canada, Quebec, and Ontario.

Panel C and D of Table 5 correspondingly report the residual diagnostic results for the VARs without and with intervention dummies. Overall, the unrestricted VARs with intervention dummies possess better innovation properties than the ones without dummies, but are inferior to their respective univariate alternatives because the BDS tests for Quebec, the JB, and the White tests for Ontario turn out to be significant at the 10% level. On the contrary, VARs with dummies have higher AICc(s) despite of their lower RMSEs. Recall that VARs are

[33] The maximum lag length for VAR/VEC models is restricted to be less than that for ARIMAs because the former contains much more parameters to be estimated.

heavily parameterized,[34] thus, quite sensitive to the introduction of new variables. The first five largest inverted Inverted AR roots are listed in Panel B of Table 6 from which we spot no root lying outside the unit circle. Yet, the magnitude of the inverted AR roots, which has already been large, rises further, particularly in Canada and Quebec. Again, the introduction of dummy variables as a means to control for structural breaks fails to generate better in-sample properties. Reasons are similar to those discussed in the preceding section.

Next, the Johansen's cointegration tests, which are available for five deterministic trend specifications[35] will be applied to the VARs in levels with intervention dummies as suggested by Joyeux (2001) because of potential shifts in the long-run relationships between endogenous variables caused by structural breaks. From a technical point of view, cointegration may exist in a system of mixed non-stationary and stationary components (see Kunst, 2009, section 4.6), but the traditional cointegrated VAR models do not accommodate any endogenous variable being purely stationary (see Kapetanios et al., 2000).[36] However, the log EIC in Canada and in Quebec, even though classified as stationary, are rather near-nonstationary because of the typically slow decay pattern in their SACFs (see Figure 2). We should bear in mind that "*near-integrated series are asymptotically stationary but behave as integrated series in finite samples*" and "*cointegration may characterize relationships between near-integrated variables*" (see De Boef and Granato, 1999, p. 102-103).[37] It is also important to emphasize that, similar to unit root tests, Monte Carlo evidence also indicates a strong association between the degree of size distortion of Johansen cointegration tests and near-integration (see Hjalmarsson and Österholm, 2007) and/or the near-non-invertibility with negative moving average structure (see Mallory and Lence, 2010) in finite samples. In addition, the existing Johansen's testing framework is not robust to the presence of exogenous variables in the sense that the conventional asymptotic distribution of the test statistics may be invalidated if dummies are added (see EVIEWS, 2009, chapter 38).

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[34] The number of parameters in a VAR with a constant included equals $p \times k^2 + k$, where p is the lag order, and k is the number of variables

[35] Analogous to a time series, which may have a non-zero mean, a deterministic trend (i.e. trend stationary) or a stochastic trend (i.e. non-stationary), a cointegration relationship may possess an intercept or a deterministic component. Johansen's cointegration testing framework is based on the five assumptions regarding the underlying trend in the data. First, there is no deterministic trend in the level series and no intercept in the cointergrating relations. Second, there is no deterministic trend in the level series but the cointergrating relations have intercepts. Third, there are linear trends in the level series but only intercepts in the cointergrating relations. Fourth, there are linear trends in both level series and cointegrating relations. Fifth, there are quadratic trends in the level series and linear trends in the cointegrating relations (see EVIEWS, 2009, chapter 38).

[36] Kapetanios et al. (2000) propose a generalization of the VEC models to include endogenous I(0) variables, whose implementation is beyond of the scope of this project.

[37] A stationary linear combination between near-integrated variables is also referred to as near-cointegration (see De Boef and Granato, 1999, p. 103).

Therefore, the Johansen tests will be conducted with dummy variables, but the decision rule will be based on the combination of the size of the log likelihood ratio (LR) statistics, the significance of the adjustment (α) coefficients, the magnitude of the largest characteristic roots, the stability and interpretability of` cointegration space (see Hendry and Juselius, 2001, chapter 9).[38] To further eliminate spurious cointegration relationships in the presence of near-integration, a series of zero and one restrictions will be respectively imposed on the β-vector, as proposed by Hjalmarsson and Österholm (2007). According to these authors, the significance of those restrictions serve to verify if the cointegration/near-cointegration relation in question describes a long-run equilibrium relationship between integrated/near-integrated series or simply represents a linear combination of stationary/near-nonstationary series.

Let us start the cointegration analysis with the examination of overlaying graphs of endogenous variables from Figure 6. It can be seen from these plots that the EIC and the UR exhibit countercyclical properties, whereas the FCPI is procyclical. In addition, they seem to suggest positive co-movements between the EIC series and the UR series, between the FCPI series and the log GDP series, and the negative co-movements between the former pair and the latter. The countercyclical nature of the UR has been known for a long time in the macroeconomic literature. The procyclicality of primary commodity prices and their relationships with respect to output and unemployment are also well documented (see Afrasiabi, 2008). It is interesting to note that the URs in January, 1997 hit the highest record level in Quebec, and the second highest in Ontario over the entire sample period. However, the associated numbers of EI claims are relatively low. This stylized fact coincides with the simultaneity of the monetary contraction and the toughening of the generosity of the EI program in 1996. The former, even though primarily aimed at inflation control, seriously impaired economic performance through the channel of inflation-unemployment trade-off (see Curtis, 2002), while the latter resulted in a considerable reduction in the EI claim volume (see section 2 of this paper).

Nevertheless, we cannot infer true cointegration relationships from preliminary visual impression because variables that look like they are "comoving" are not necessarily cointegrated (see Hendry and Juselius, 2001, section 1). The cointegration exercise will be performed on the basis of the most popular assumptions that the

[38] Hendry and Juselius (2001), chapter 9 also suggest to visually investigating the evolution of the test statistics through time, which are expected to exhibit linear trends for the first r cointegration components, and remain roughly constant for the rest. This diagnostic tool is ignored here because the large VAR orders relative to the sample size will introduce more bias to the test results when test statistics are recursively computed over subsample periods.

data contain uniquely stochastic trends, and the cointegration relations have only an intercept.[39] The left panel of Table 8 (columns 2 to 8) illustrates the formal tests to determine the cointegration rank (r) using the maximum eigenvalue statistics, as suggested by Hjalmarsson and Österholm (2007) because of their robustness toward near-integration. The right panel of Table 8 (columns 10 to 11) displays the F-statistics and the associated p-values in parentheses upon imposing zero and one restrictions on the corresponding cointegration (β) coefficients of the log EIC in Canada and Quebec. These series are statistically proven to be stationary by the ERS unit root tests, and cointegration relations may purely arise from their stationarity. As we can see, the joint restrictions are rejected at the 5% level in Quebec, but are not in Canada. This implies that the first cointegration vector in Canada, whose space is uniquely spanned by the log EIC series, does not represent a true cointegration relation.

The first five largest inverted characteristic roots for the VAR/VEC(s) in Canada, Quebec, and Ontario are listed in columns 1, 5, and 8 in Table 9 when $r = 0$ (i.e. no cointegration), in columns 6 and 9 when $r = 1$ (i.e. one cointegration relation), in column 2 and 11 when $r = 2$ (two cointegration relations). The t-statistics of the α-vector for the first cointegration relation (α_1), and the second cointegration relation (α_2) are corresponding shown in columns 7, 10, and the pairs of columns 3-4 and columns 12-13. Other possible cases are ignored because the largest inverted AR roots get closer to unity, and most α-coefficients are statistically insignificant. As asserted in Table 9, the inverted AR roots grow bigger, and the proportion of α-coefficients that are insignificant at the 5% level become larger, especially when $r = 1,2,3$ for Quebec and $r = 2,3$ for Ontario.

Figure 7 depicts the cointegration spaces of Canada (with restrictions applied), and Ontario when $r = 1$. There is evidence supporting the non-stationarity, i.e. the instability of two cointegration relations in Canada by the ERS unit root tests (p-statistics = 6.0287, and 17.1323; 10% critical value = 4.2708).[40] On the contrary, we strongly reject the null hypothesis of unit root at the 1% level for Ontario (p-statistic = 1.5155, 1% critical value = 1.9240).

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[39] This choice is made on the grounds that most of variables in this project have non-zero means, and none is found to be trend stationary (see section 6.1 of this paper).

[40] These cointegration relations involve near-nonstationary series, thus, should be validated against an efficient unit root test like the ERS.

As such, this cointegration testing exercise cannot rule out the existence of one long-run relationship in Ontario, but none in Canada and Quebec. Residual checks for the appropriateness of the cointegrated $VAR(4)$, i.e. $VEC(4)$, in Ontario is provided in Panel E of Table 5. Even though the assumption of normality is rejected at the 5% level, this non-normality characteristic primarily originates from the excess kurtosis (significant at the 5% level) to which the statistical inference is much less sensitive (see Hendry and Juselius, 2001, chapter 3). Otherwise, the VEC dominates its unrestricted VAR in terms of both AICc(s) and RMSEs as shown in the middle panel of the same table.

Since the interpretation of individual coefficients from a VAR or a VEC is extremely difficult, the analysis of dynamic structure of these systems will involve instead the examination of the Granger causalities, the impulse responses, and the variance decompositions (see Stock and Watson, 2001). Estimation of the cointegration space (β) and the adjustment space (α) is given in Table 10. Careful examination of the β-vector, which represents the stationary linear combination between endogenous variables, is unnecessary because "*cointegration between variables is a statistical property of the data that only exceptionally can be given a direct interpretation as an economic steady-state relation*" (see Juselius, 1999, p. 279-280). Yet, significant adjustment coefficients such as those in the equation of EIC, FCPI and UR capture the extent to which the variables deviate from equilibrium. Therefore, they imply the existence of long-run causalities in the Granger sense but cannot reveal the exact direction of causality. The magnitude of these coefficients measures the speed at which each variable converges toward their long-run equilibrium value after a shock to itself. The bigger is the magnitude, the faster is the convergence. Negative α-coefficients, (i.e. the case of EIC and FCPI) imply downward adjustment to restore the long-run relationship, while positive ones (i.e. the case of UR) indicate an upward adjustment along the steady-state path (see Ansari and Ahmed, 2007).[41] As such, Table 10 reveals the evidence that changes in EIC (i.e. log EIC), FCPI (i.e. log FCPI) and UR (i.e. log UR) adjust to their means respectively by 36%, 5%, and 11% of the temporary deviation from the steady-state in the preceding period. The long-run Granger-causality testing, which is based on the joint significance of the

[41] The α-coefficients in a bivariate VAR are expected to be negative to ensure the stability of the system convergence towards the steady-state. Otherwise, short-run adjustments are digressive because of overreactions. However, this condition does not need to apply for VARs consisting of more than two variables due to mutual feedbacks between various independent variables (see Ansari and Ahmed, 2007).

coefficient of the error correction term and those of the lagged differences of a right-hand-side regressor, suggests the inverse causality from GDP and FCPI to EIC and UR.[42]

Table 11 summarizes short-run Granger-causality results of the four-variable $VAR/VEC\{EIC, GDP, FCPI, UR\}$. It contains the F-statistics and the associated p-values that determine whether the knowledge of past values (i.e. lags) of the regressor(s) implied by the column label (columns 2 to 6 for Canada, 7 to 11 for Quebec, and 12 to 16 for Ontario) helps to improve considerably the prediction of the dependent variable referred by the row label. From this table, we observe strong evidence supporting the mutual feedback (at the 5% level) between the EIC and the GDP across national and provincial levels. Statistical evidence also supports the bidirectional causalities in the Granger sense, at the 5% level, between the EIC and the FCPI in Canada and in Ontario, between the GDP and the FCPI in Quebec and Ontario. FCPI appears to be a useful predictor of EIC in Canada and Ontario but not in Quebec. Conversely, UR displays insignificant predictive power for all other variables. In addition, there are pairs of Granger independent variables such as EIC - UR in Canada and Quebec, and FCPI – EIC in Quebec. However, with the presence of cointegration relationship, short-run Granger causalities between endogenous variables in the Ontario VEC exist in at least one direction.

The sign, the shape, and the timing of the interrelationship between endogenous variables and short-run adjustments in a VAR/VEC system is investigated by means of generalized impulse functions, which does not require orthogonalization of innovation shocks and is invariant to the ordering of variables. Figure 9 depicts the impact of a one-standard deviation positive innovation shock originating from one variable on the other using a window of 24 months. In general, the responses die out after one year in the Canada and Quebec VARs, and converge to the steady-state roughly after 15 months in the Ontario VEC, demonstrating the stability of these models. In addition, the directions of impacts appear to be very similar across national and regional levels, and quite consistent with the economic theory. For example, the negative association between the UR and the GDP has been long documented and referred to as the Okun Law. The observed positive relationship between the FCPI and the GDP and the negative impact of the FCPI on the UR are also theoretically grounded. According to the neoclassical theory of general equilibrium, a soaring price of a commodity will boost the output of that commodity and dampen the output of some other commodity. For a net exporter of raw materials

[42] Refer to Zestos and Tao (2003), p. 867-872 for detailed discussion of how to implement long-run Granger causality testing. For the sake of brevity, test statistics are not presented but available upon request.

and energy like Canada, this situation will apparently lead to an increase in exports, hence, a rise in GDP and a decline in UR.

Consistent with the Granger causality analysis, shocks from the UR of three VAR/VEC(s) have marginal effects on other variables. The maximum impact on the GDP from FCPI innovations occurs during the fourth month in Canada and Quebec and at the ninth month in Ontario. On the contrary, FCPI responds to a GDP shock by an initial increase during the second period in Canada and Quebec, which tapers off after the following month. In Ontario, the FCPI adjusts upward gradually towards the long-run equilibrium. The full impact of one standard deviation innovation shocks from the FCPI on the EIC are realized after seven months in Canada (1.8% reduction), eight months in Quebec (0.9% reduction), and 7 months in Ontario (3.2% reduction). One standard deviation innovation shocks from the GDP to the EIC reach the maximum strength during the fifth month in Canada (1.2% drop) and Quebec (1.7% drop), and the fourth month in Ontario (3.9% drop). It is worth noticing that these impacts become considerably stronger when cointegration exists in Ontario. Possible explanation for this phenomenon is that as the most populous province, Ontario shares roughly 40% of Canada's GDP in 2010 and accounts for almost 60% of total national manufactured exports (see OMF, 2011). As such, it is quite expectable that innovative shocks originating from both GDP and FCPI will have larger effects on this province.

Nevertheless, the reverse relationships, i.e. the effects of the EIC shocks on the GDP and the FCPI, are found to be positive in Canada and Quebec. These apparently contradict prior findings in the literature, which supports the evidence of negative association between the UI claims and the economic activity (see Gavin and Kevin, 2002). Appearing puzzling, the results are not worrisome, according to my judgement, because the full impacts are barely significant. Note that the similar conflicting association is not observed in the Ontario VEC, where cointegration presents. Indeed, it may be the adverse consequence of misspecification bias associated with the omission of moving average components in the VAR systems (see Demers and Dupuis, 2005).[43]

The relative strength of different influences on a given variable can be judged through the variance decomposition. Table 13 presents a brief summary of the proportions of error variance made in forecasting a

[43] Demers and Dupuis (2005) conduct forecasting exercises for the Canadian GDP growth using the VARMAX modeling approach. By contrasting predictive results from these models with their nested alternative VARXs, these authors demonstrate that ignoring the MA dynamics may seriously affect the parameter estimates and result in significant deterioration of forecast performance, notably if the series in question exhibits large range of serial dependence.

variable referred by the row label that can be attributed to the innovations to each of the regressor(s) implied by the column label (columns 3 to 6 for Canada, 8 to 11 for Quebec, and 13 to 16 for Ontario), including the variable in question itself. Forecast horizons are indicated in columns 2, 7, and 12. In general, we observe low level of interactions among variables in the Canada and Quebec VARs, except the case of EIC in Canada, implying a high dependency of the future path of each series on its own past history. In short, these findings are consistent with those of the impulse response functions, where the magnitudes of most VAR responses are small and barely statistically significant. Conversely, the interactions between variables are found to be considerably stronger in the presence of cointegration. Specifically, the relative contributions of other variables to the prediction of the Ontario UR account for 75% of its forecast variance at the 12-month-horizon. They also suggest the importance of the GDP and the FCPI in projecting the EIC, which respectively capture 54.56% (17.67% from GDP, 37.89% from FCPI), 37.49% (29.30% from GDP, 8.19% from FCPI) and 43.73% (28.01% from GDP, 15.72% from FCPI) of the EIC forecast variability in Canada, Quebec, and Ontario at the twelve-months horizon.

As mentioned above, the VAR/VEC modeling framework is potentially subject to misspecification bias. Merely relying on AR structures to approximate the serial dependence in the data may not adequately account for the long persistence induced by structural breaks and outliers. Nonetheless, the building of VARMA models, which require relatively long samples for a reliable model identification and estimation, is empirically impossible in this study due to limited data availability. In addition, as mentioned in Hjalmarsson and Österholm (2007), systems involving near-integrated series are prone to spurious regression results induced by their mimicking of the behaviour of nonstationary data. Consequently, the Granger causality tests, the impulse response functions and the variance decomposition might contain misleading results due to estimation bias, thus, should be interpreted with caution.

Table 12 compares the in-sample fits between the ARIMA (columns 2 to 7) and the corresponding VAR/VEC (columns 8 to 13) for the three log EICs on the basis of the log-likelihood (LOGL),[44] the RMSE, and its decomposition. It is worth noticing that the Canada VAR requires the longest lag order (equal to six) in order to yield adequate fits, probably because the major structural change in 2008 manifests itself most profoundly in

[44] The log-likelihood can be used as a measure for the goodness-of-fit in with higher value implying better fit (see Phillips, 1991)

its demand for EI benefits. On the other hand, the excessive fluctuations in the Quebec log EIC also seriously affect the fitting capability of the Quebec VAR, which is shown to be inferior to its ARIMA counterpart, visually through the plots of actual vs. fitted in Figure 8, and statistically according to the measure of LOGL (lower), and the error variance (larger) from Table 12. The in-sample performance of the Canada VAR is ambiguous because it has higher LOGL and lower RMSE but slightly higher VARP. Only the Ontario VEC strictly surpasses its ARIMA benchmark in all selected criteria.

6.4. Out-of-Sample Evaluation

The two alternative modeling approaches, the univariate ARIMAs and the multivariate VAR/VEC(s), are used for forecasting exercises for which attention is paid primarily to the predictive accuracy rather than the estimation of the true DGP. Even though these models are not ideal forecasting tools, they have the advantages of being simple and closed in the sense that they consist of uniquely endogenous variables, and their predictions do not depend on the quality of forecasting input variables. Yet, they are prone to over-parameterization, particularly the VARs. Thus, the estimation of these models is exposed to a great deal of parameter uncertainty. As such, for forecasting purposes, the negative effects of structural breaks will be tackled by the techniques of rolling window regressions and combining forecasts (see sections 3, 4.1 and 4.5 of this paper) instead of by intervention dummies, given the deficiency of the latter method and the small size of the specification subsample (only 108 observations). In addition, the maximum lag order in the VARs is restricted to four, and insignificant parameter estimates at a given lag are jointly eliminated by means of the lag exclusion tests.

Simulated real-time prediction results for the EI claims at all national and provincial levels over the three selected forecast horizons, ranging from one-month-ahead, six-months-ahead, and twelve-months-ahead, are respectively presented in Table 14, Table 15, and Table 16. Columns 2 and 3 indicate the modeling classes and the corresponding information sets. The five measures of forecast accuracy, the RMSE, the MAE, the U-Theil, the CI, the DA, and their associated ranks are presented from columns 4 to 13. The two hypothesis test statistics are reported in columns 14 and 15. Evaluation results for each forecasting horizon are organized in seven categories, the baseline ARIMAs, the top winners, the strict winners/losers, the weak winners/losers, and the mixed models. The strict winners/losers are defined as models whose predictive performance is strictly above/below the benchmark in terms of all five evaluation criteria. The weak winners/losers refer to those which do not underperform/outperform the benchmark in any measure. The top winners consist of those who appear to be the best among strict winners. Finally, mixed models imply those who may dominate the baseline model in some respects but are surpassed by this one in some others. For a given geographical entity, models in shaded areas are those who achieve absolute improvement across the three forecast horizons.

The first remark is that most of the HLN tests of forecast encompassing are significant, while the majority of DM tests of equal forecast accuracy are not, even for some top winners. This finding agrees with the observation from Busetti et al. (2009) that the former tends to have higher rejection rates than does the latter (see section 4.5.1 of this paper). More questionably, the HLN tests sometimes reject the null hypothesis of no significant enhancement achieved from combining the benchmark with the competitor model, although the latter is strictly inferior to the former in terms of all five assessment criteria. These conflicting results may be the consequence of size distortion in finite samples, given that the tests are quite sensitive to the assumption of normality of forecast errors (see section 4.5 of this paper), which may be seriously impaired by the presence of structural changes and large variability in the three EIC series. Nevertheless, such a contradictory situation is not observed in DM tests, which are empirically proven to be more robust to non-normality (see Harvey et al., 1998). Therefore, inferences about forecast accuracy in this study are primarily drawn from the DM hypothesis testing.

6.4.1. ARIMA Forecasts

ARIMA models are ranked very low in the three geographical entities. Yet, the ARIMA framework seems to provide better prediction of directional change, particularly at one-month-ahead and six-months-ahead horizons in Canada. ARIMAs are also average-ranked in the MAE sense over the period of six-months-ahead in Canada, and twelve-months-head in Quebec. Conversely, six-months-ahead forecasts from the Quebec ARIMAs, and twelve-months-ahead forecasts from the Ontario ARIMAs, are bottom-ranked in four out of the five criteria.

Relative to the random walk, i.e. the "no change" models, the U-Theil statistics reveal the underformance of the ARIMAs across the three forecast horizons in Ontario, and over the period of six-months-ahead in Quebec.

6.4.2. VAR/VEC Forecasts

Cointegration/near-cointegration relations are detected in several specifications across all national and provincial levels. More specifically, 15, 19, and 40 cointegrated VAR models are respectively constructed for Canada, Quebec, and Ontario. Thus, we observe fewer long-run relationships in Quebec, where near-integration exists, and particularly much less in Canada, where near-integration is coupled with profound structural changes. In Ontario, where cointegration relations present most often, the multivariate error correction modeling approach seems to remarkably boost up the relative forecast performance with respect to the ARIMA benchmark. The proportion of strictly winning VECs in this province are correspondingly 78%, 95%, and 100% at one, six and twelve-months-head horizons, whereas only roughly 55% of Canada VECs are classified as strict winners at each forecast horizon of concern. In contrast, the proportion of strictly losing VEC(s) over the period of six-months-ahead in Canada attains the highest level (40% of all VECs) and becomes much higher to that of losing VARs (14.3% of all VARs)

There always exist strictly winning VAR/VEC alternatives, the number of which increases substantially as the forecast horizon is prolonged. One exception is the case of twelve-months forecasts in Quebec, which is probably induced by the large variability of the EIC in this region. However, the gap in the forecast error losses, according to the DM tests, drops considerably with the horizon length. This multivariate framework specifically exhibits the best predictive ability in Quebec over short-term horizons, where the rejection rates of DM tests occur most frequently. The majority of VAR/VEC(s) surpasses the ARIMA baseline in Ontario, where 80%, 92% and 98% of them are respectively counted as strict winners at one-month-ahead, six-months-ahead, and twelve-months-ahead horizons. Despite of the fact, the loss differentials are not significant in most cases. Furthermore, the predictive performance of the VAR/VEC(s) seems to particularly suffer over longer horizons such as six-months-ahead in Canada and twelve-months-ahead in both Canada and Ontario, where none of them is statistically superior to the benchmark.

Only a few VAR/VEC(s) are classified as strict losers, one (or 2%) at one-month-ahead in Ontario, two (or 4%) at one-month-ahead, and 11 (or 22%) at six-months-ahead in Canada, but none is found in Quebec. As we can see, all of these models are comprised of a labour market indicator, which is either the NEO or the UR, in their information set. Most of them also contain the IRS. It is worth noticing that according to the Granger causality tests and the variance decompositions,[45] these variables have low predictive power with regard to the EIC, even though their inclusion contribute to the overall goodness-of-fit and/or forecasting ability in several instances.

Recall that the ARIMA benchmark for Ontario is dominated by the random walk model in the U-Theil sense. Accordingly, we observe a higher fraction of VAR/VEC(s) with the associated U-Theil above unity, which are reported as 10%, 16%, and 12% respectively at one, six, and twelve-months-ahead horizons. Furthermore, among those whose forecast ability is considered as being inferior to the random walk, the proportions of VAR(s) are generally higher than VEC(s). Another remark is that the forecast accuracy of all Ontario VAR/VEC(s) in terms of RMSE, MAE, and U-Theil statistics is consistently lower than that of the Canada and Quebec counterparts despite comparable measures of respective directional accuracy. Finally, no loser with regard to the "no change" model is found at six-months horizon for Quebec and at twelve-months horizon for both Canada and Quebec.

As we can see, some specifications provide the predictive superiority over longer horizons at the cost of their short-term forecasts. For example, the 12th specification $\{EIC, CCLI, IRS, UR\}$ strictly outperforms the ARIMA benchmark at twelve-months-ahead for Canada, at six and twelve-months-head for both Quebec and Ontario. Nevertheless, its forecast ability at shorter forecast horizons seriously suffers, as it always appears in the bottom classification as either mixed models or strict losers. In contrast, some others are better in short-term projections. The 31st specification $\{EIC, CCI, FCPI, IRS\}$ for instance, is considered as the strict winner at one and six-months-head for both Canada and Quebec but is unable to surpass the benchmark in all five evaluation criteria over the twelve-months-ahead horizon. Overall, the numbers of dominating models in each geographical entity over the three forecast horizons of interest are in ascending order: five for Canada, 15 for Quebec, and 39 for Ontario. Above all, the 23rd specification $\{EIC, CCLI, FCPI, IRS\}$ consistently dominates the respective baseline ARIMAs across national and provincial levels.

[45] Because of limited space, the results of these tests are not reported but available upon requests.

6.4.3. Combined Forecasts

As described in section 4.5, the five different forecast combination schemes, the MEAN, the MEDIAN, the MRBEST, the FOCUS, and the DMSE, are shown to be quite promising in face of the great uncertainty induced by near-integration, specification bias, and structural changes. In general, predictive results obtained from the combination of forecasts appear very similar to the ones from the VAR/VEC framework. Yet, the significance of the loss differentials occurs much more often, suggesting their better performance relative to forecasts from a single model.

The FOCUS and the set of the other four weighting schemes (i.e. the MEAN, the MEDIAN, the MRBEST, and the DMSE) are respectively declared as outperformers across the three short and medium-term forecasting horizons in Quebec and Ontario. The FOCUS is the only one surpassed by both the baseline ARIMA and the "no change" random walk at one-month horizon for Canada. Consistent with previous studies, the two simplest weighting schemes, the MEAN and the MEDIAN, work pretty well, especially in Ontario, where they dominate both the ARIMAs and the random walk over all three interested horizons. However, no single pooling approach is able to consistently outperform the benchmark across all national and provincial levels.

6.4.4. Selection of Champion Models

In overall, both individual forecasts generated from the VAR/VEC modeling framework and combined forecasts perform pretty well. However, the forecast error losses tend to worsen with the lengthening of forecast horizons, as we observed substantial jumps in the values of RMSE, MAE and U-Theil, especially from one to six-months horizons, during which the error losses doubled on average. The results also suggest that a model that is superior in terms of forecast accuracy may be inferior with regard to directional accuracy. This situation, which is particularly true for Quebec, notably at medium-term horizon, may explain the obvious reduction in the number of strict winners relative to other shorter horizons. In addition, as discussed earlier, some models may dominate the benchmark in long-term projections but become dominated over short-term ones, and vice versa. On the other hand, some models possess the best predictive power in a given geographical entity, but their forecast performance may deteriorate when applied to others. Consequently, it is often difficult to discern the champion among a set of candidate models.

Figure 10 illustrates the short-term and medium-term predictions from tentatively selected top-ranked models. These are the $VAR47\{EIC, CCI, FCPI, UR\}$, the $VEC49\{EIC, CCI, IRS, UR\}$, and the FOCUS for Canada; the $VEC19\{EIC, GDP, CCLI, CERI\}$, the $VEC04\{EIC, CCLI, IRS, NEO\}$, and the $VEC22\{EIC, CERI, FCPI, IRS\}$ for Quebec; the MEAN, the $VEC23\{EIC, CCLI, FCPI, IRS\}$, and $VEC48\{EIC, FCPI, IRS, UR\}$ for Ontario, respectively at one, six, and twelve-months horizons. First, it is worth noticing that apart from the exception of the $VAR47\{EIC, CCI, FCPI, UR\}$ chosen for Canada at one-month-ahead, the remainder of these champion models are either VECs or combined ones. Second, the visual examination of the plots of actual v.s. predicted reveals a quick deterioration of forecasts along forecast horizons, which is specifically aggravated during the phase of unexpectedly sharp increase in the demand for EI benefits starting in mid-2008. Projections over this period significantly lag behind and drag under the actual series, particularly in the case of twelve-months-ahead forecasts for Ontario, indicating the forecast failure when a sudden structural break eventuates. Hence, the quality of predictions seems to be adversely affected by structural changes.

It is obvious from the preceding analysis that the three modeling classes, the ARIMAs, the VAR/VEC(s), and the combinations, behave differently when applied for forecasting in Canada and the two provinces considered because of the distinctive characteristics possessed by their EI claims behaviour. However, it is difficult to disentangle the effects of each of these factors on the forecasting ability of the investigated models. As an important note, the attempt to redo the entire forecasting experiment using uniquely unrestricted VARs shows that the overall results are quite robust to the omission of cointegration relations.[46] Overall, we observe a considerable reduction in the performance gap with respect to the benchmark ARIMAs in the presence of profound structural shifts. The predictive ability of the Quebec VAR/VEC(s) over medium-term horizon is also greatly impaired, probably because of the excessive variation in the respective log EIC. Nevertheless, the forecasting accuracy of the Ontario VAR/VEC(s) relative to the "no change" models suffers, particularly at the medium-term horizon. This finding seems to conflict with the fact that Ontario experiences less accentuated breaks than Canada and lower degrees of data variability compared to Quebec. Recall that the Ontario log EIC exhibits a long and persistent memory that typically presents in a fractionally integrated process (see section 6.3.1 in this paper). Further formal testing, which is beyond the scope of this study, needs to be carried

[46] Because of limited space, these results are not reported but available upon requests.

out in order to confirm the evidence of fractional integration. If it is true, fractional integrated/cointegrated VAR models should be used in place of the standard VAR/VEC approach (see section 3 of this paper).

7. Policy Implications

The volume of EI claims has profound implications for the quality, the accessibility, and the cost of the EI program. Estimation of future demand for EI benefits may become a constructive tool for policy makers and program administrators in making rational choices between policy options related to the EI program administration and the EI service delivery. From section 6.3.2, we find evidence for the countercyclical properties of the EIC series from both visual inspection and impulse response functions, and the existence of Granger-causalities from GDP and FCPI to EIC in both short-run and long-run. The negative relationship between the GDP and the EI claims reflects that a contraction of the output is associated with a short-term expansion in demand for EI benefits and vice versa. In-sample results also highlight the negative contribution of commodity prices in explaining the future evolution of the EI claims. These empirical results have important implications for resource planning and policy formulation within HRSDC or more specifically, Service Canada. For example, during the recession or the period of low commodity prices, it is hard to justify staff reduction or facility closure policies without recourse to other cost effective service options such as on-line accesses and automated processing procedures in order to face a higher demand for EI benefits in the coming periods. Moreover, the lower is the level of EI claims suggested by future projections, the harder it is to support the position that a tighter benefit eligibility/entitlement policy is needed to reduce the future claim volume, or that an EI premium increase policy is necessary to reduce the cost of the program. On the other hand, during the periods of output expansion, it might be advisable to rather preserve the redundant staff/resources and dedicate them to modernize the service delivery system in anticipating for an eventual rise in the number of claims during the next economic downturn.

However, these VAR/VEC forecasting models are estimated in reduced form and not appropriate to explicitly derive the direction as well as the magnitude of effects that a change in policy stand potentially generates. We should bear in mind that these systems involve uniquely endogenous variables, hence, are unable to isolate contemporaneous causal links. On the contrary, VAR/VEC models in structural form, which use either economic theory or institutional knowledge to identify contemporaneous relationship among variables, allow the interpretation of correlations as causalities. Yet, in order to sort out causal links, this variant of the VAR/VEC approach requires that certain restrictions need to be imposed on the correlation matrix. These, in turn, heavily rely on prior assumptions, and thus, might eliminate some useful predictive information contents. As such, structural VAR/VEC(s) are more suitable for policy analyses than for forecasting purposes (see Stock and Watson, 2001).

8. Conclusion

This study is primarily motivated by the necessity of building adequate forecasting models for the EI workloads in order to assist Service Canada in maximizing the quality of its service delivery, especially during periods of economic downturn. Reliable predictions for the EI claim volumes will aid policy makers and program administrators to formulate performance policies and plan for resource requirements. To serve this purpose, eight potentially relevant predictors for the EI claims, the unemployment rates, the Net Employment Outlook, the Canadian Composite Leading Indicator, the GDP, the interest rate spread, the Fisher Commodity Price Index, the Canadian-dollar Effective Exchange Rate Index, and the Consumer Confidence Index, are explored in a simulated real-time, out-of-sample forecasting using the standard VAR/VEC approach. Finally, five simple combination procedures widely employed in the literature to pool individual forecasts are exploited in order to mitigate the problems posed by specification bias, structural changes and near-integration.

Despite the fact that the in-sample analysis suggests evidence of near-integration, structural changes and large variation in the demand for EI benefits, out-of-sample findings are pretty favourable, highlighting the trade-off between estimation bias and variance of forecast errors. According to the assessment of forecasting performance, the VAR/VEC framework provides reasonably good predictions in the sense that there always exists a subset of VAR/VEC models dominating the benchmark ARIMAs over both short-term and medium-term horizons for a given geographical entity. The 23rd specification, whose information set is made up of the EI claims, the Canadian Composite Leading Indicator, the Fisher Commodity Price Index, and the interest rate spread, is found to be the overall strict winner at all national and provincial levels. Moreover, consistent with previous studies, forecasting results also confirm the adequacy of the two simplest combination schemes, the MEAN, and the MEDIAN, which succeed to surpass the benchmark in several cases. The FOCUS weighting scheme is classified as a strict winner in Ontario, and so are the other four pooling strategies, the MEAN, the

MEDIAN, the MRBEST, and the DMSE, in Quebec across the three horizons of interest. The higher proportion of pooled forecasts that is significantly superior to the benchmark in the loss differential sense for any given geographical entity at any horizon of interest indicates the effectiveness of forecast combination strategies in the presence of structural changes and near-integration. In overall, forecasts from a single VAR/VEC model and their combinations work best in Quebec, where at least one of these competitors is significantly outperform the ARIMA baseline in the RMSE sense at the 10% level or below over a given forecast horizon, and none is classified as strict losers.

However, the forecast ability deteriorates quickly as forecast horizons grow, particularly upon switching from short-term to medium-term. It also appears that near-integration, structural changes and large variability adversely affect the quality of predictions. More specifically, the performance relative to the ARIMA benchmark suffers in Canada, where profound structural changes occurs, and in Quebec medium-term forecasts, where excessive fluctuations are observed. In Ontario, while frequently occurring cointegration relations seem to boost up the predictive power of the VAR framework to certain extent, the presence of high time-dependent persistence in the EI claims considerably degrade the overall performance of all models comparative to the "no change" situation in the U-Theil sense. The DM tests of equal forecasting ability indicate no significant predictive enhancement with respect to the ARIMA benchmark from either using VAR/VEC competitors or their pooling alternatives at six-months-ahead horizon in Canada, and over the period of twelve-months-ahead in both Canada and Ontario. Thus, one possible direction for future research is a further investigation of whether this series follows a fractionally integrated process. If yes, the fractionally integrated/cointegrated VAR approach would be more suitable and promising for forecasting exercises in this province.

Given that the conventional VAR/VEC framework do not constitute an ideal modeling technique, particularly in case of structural changes and large variability, a wide range of other empirically-proven better approaches include non-linear modeling methodologies have been proposed in the literature (see section 3 of this paper). Nevertheless, an unprecedented event like the record-breaking high demand in EI benefits occurring in mid-2008, i.e. beyond the estimation subperiod from January 1997 to December 2005, make the potential success of the latter alternatives much less likely, unless the break itself can be otherwise predicted.

The final suggestion for future researches involve the exploration of the VAR/VARMA models in structural forms with the inclusion of various administrative parameters of the EI program in order to enable appropriate analyses of the impact of a policy-imposed change and its effectiveness on the program administration and performance management.

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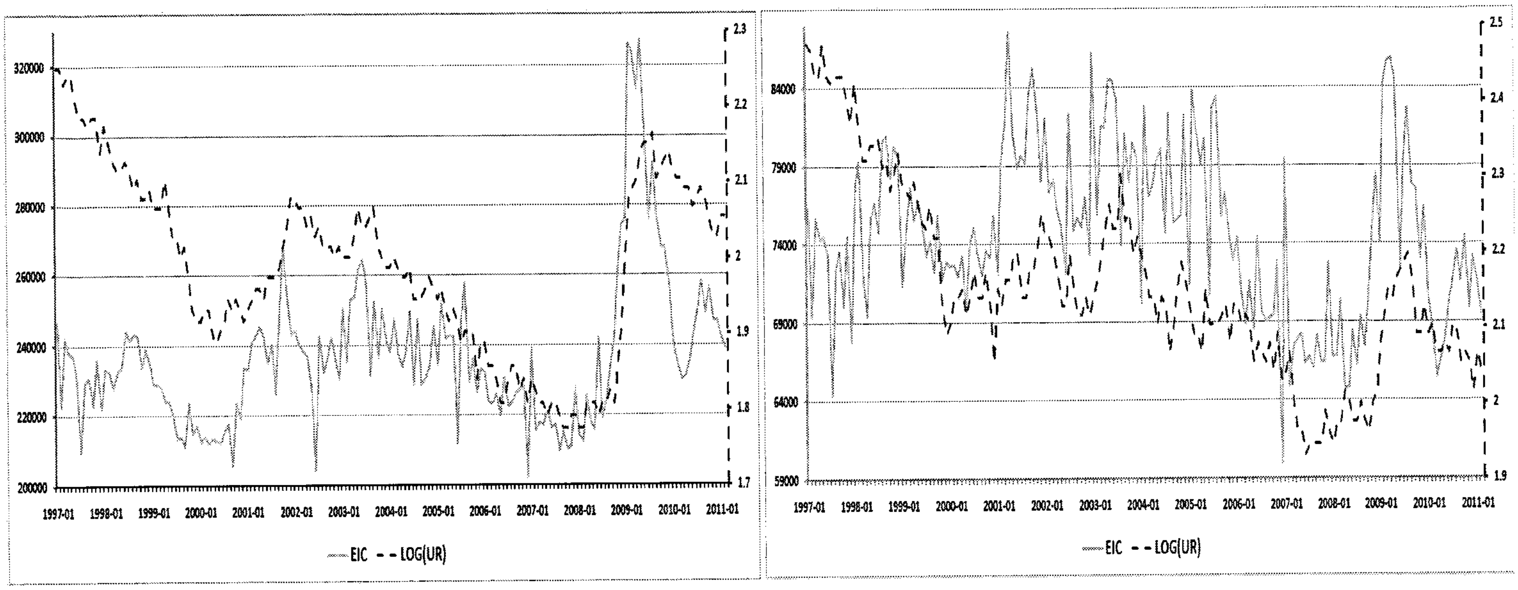
Appendix A: Figures

Figure 1: EI Claims (EIC) v.s. Unemployment Rates (UR) – Monthly and Seasonally Adjusted



Canada (CA) Quebec (QC)

Figure 2: Correlograms of Selected Series

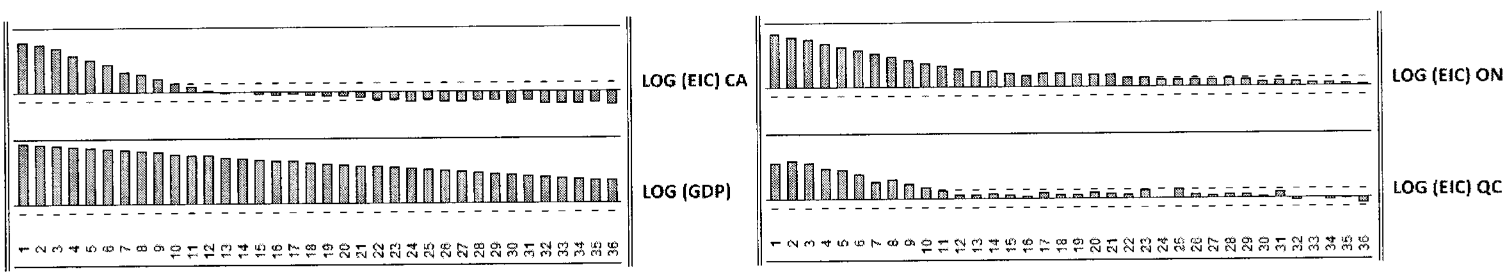


Figure 3: Log (UR) in First Difference

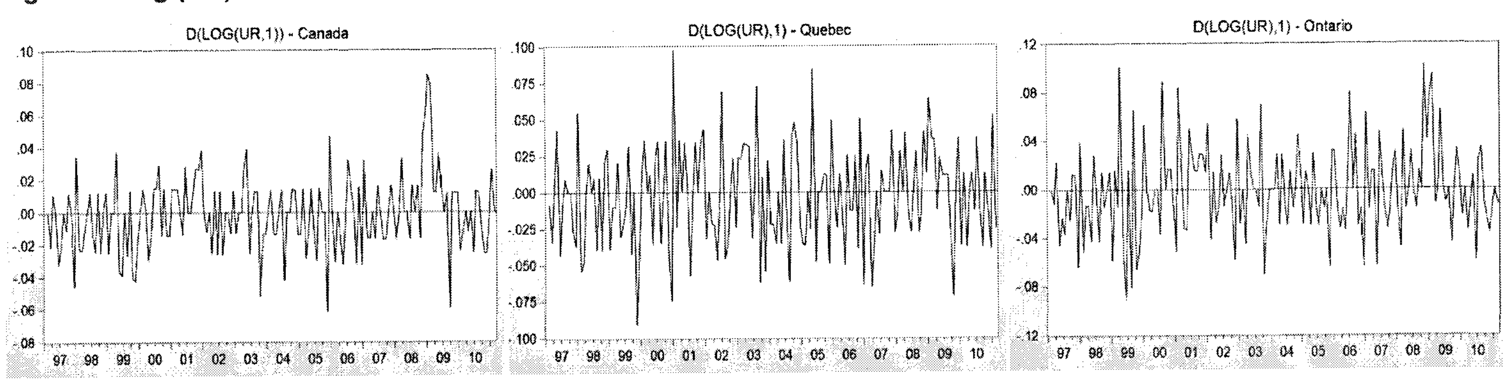
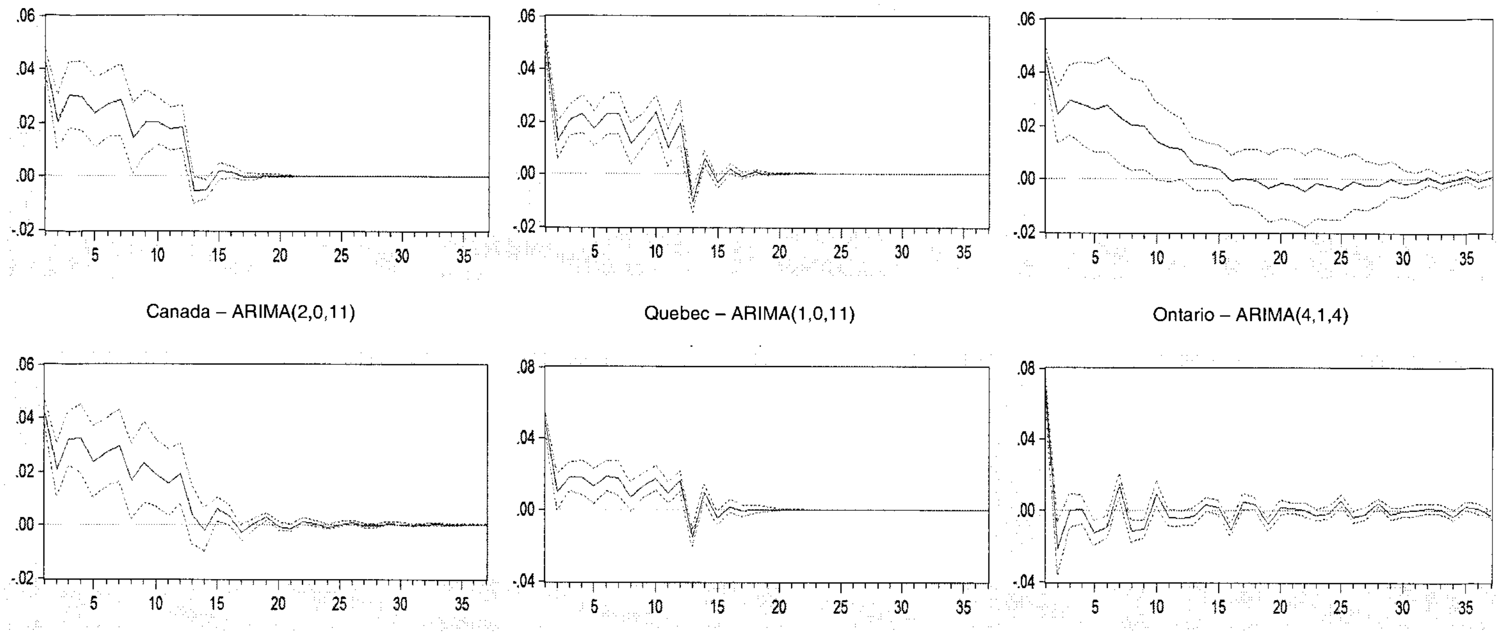


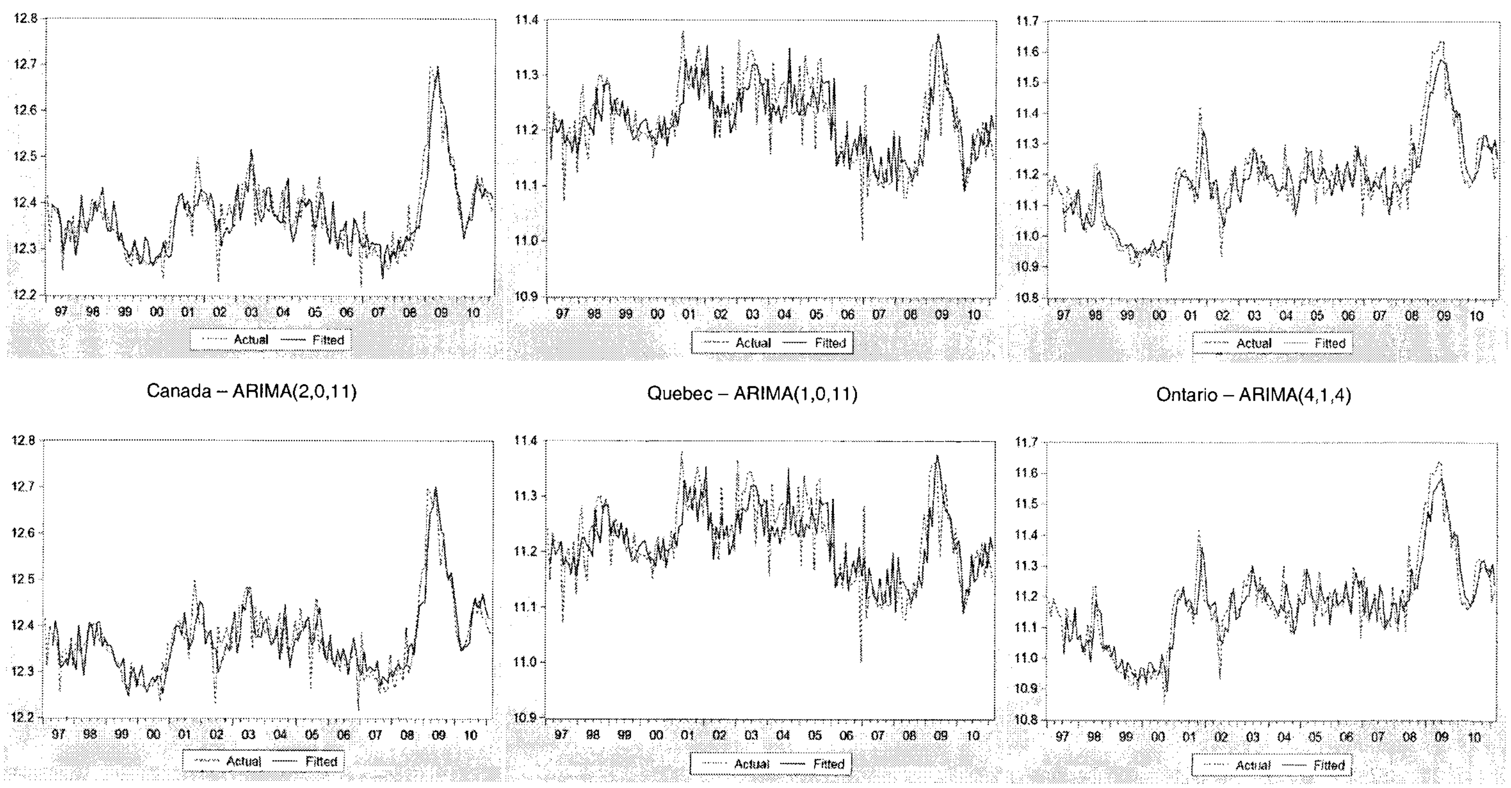
Figure 4: Impulse Responses +/- 2 S.E. from ARIMA Models



Canada – ARIMA(2,0,11) | Quebec – ARIMA(1,0,11) | Ontario – ARIMA(4,1,4)

Canada - ARIMA(3,0,11) – with dummies | Quebec - ARIMA(2,0,11) – with dummies | Ontario – ARIMA(5,1,6) – with dummies

Figure 5: Actual/Fitted Log-level EIC from ARIMA Regressions



Canada – ARIMA(2,0,11) | Quebec – ARIMA(1,0,11) | Ontario – ARIMA(4,1,4)

Canada – ARIMA(3,0,11) – with dummies | Quebec – ARIMA(2,0,11) – with dummies | Ontario – ARIMA(5,1,6) – with dummies

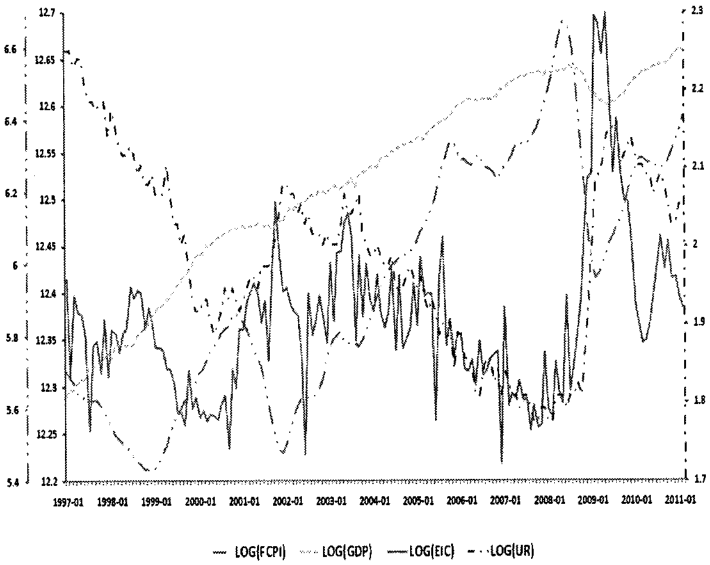
Notes:

The actual and fitted series are in log-level.

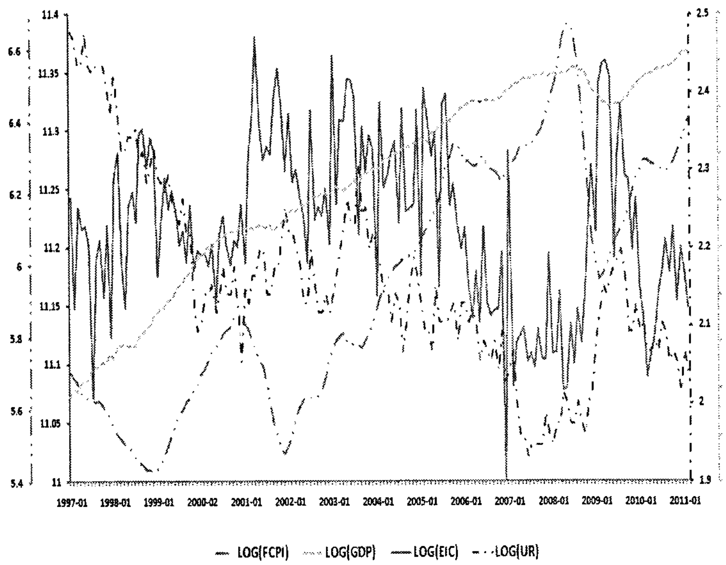
The regression residuals are in log-level for Canada, Quebec and in log-first-difference for Ontario.

Standardized Residuals is the normalization of the regression residuals by its standard deviation (see Eviews, 2009, p 18).

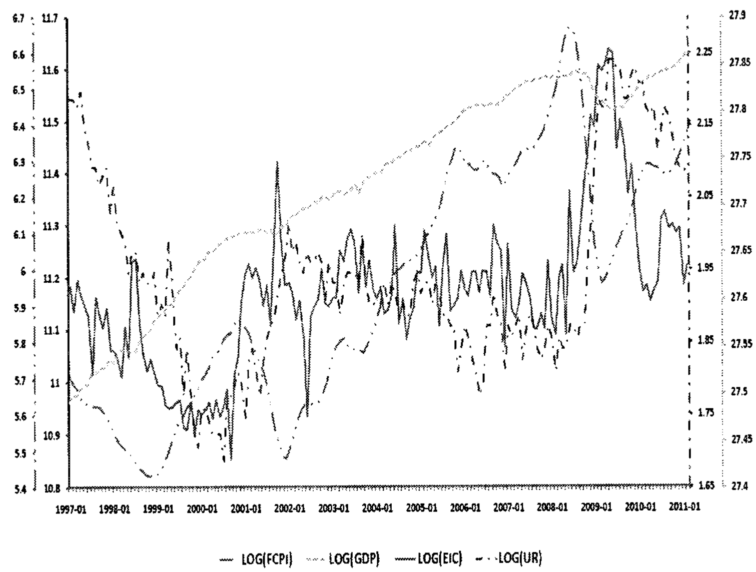
Figure 6: Overlay Plots of Endogenous Variables in VAR{EIC,GDP,FCPI,UR} Models



Canada

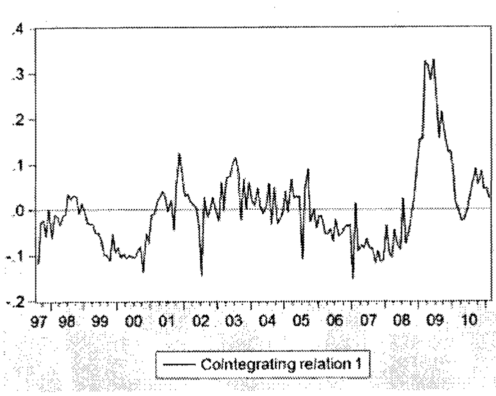


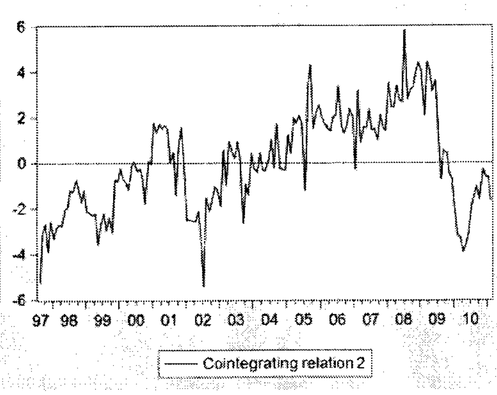
Quebec



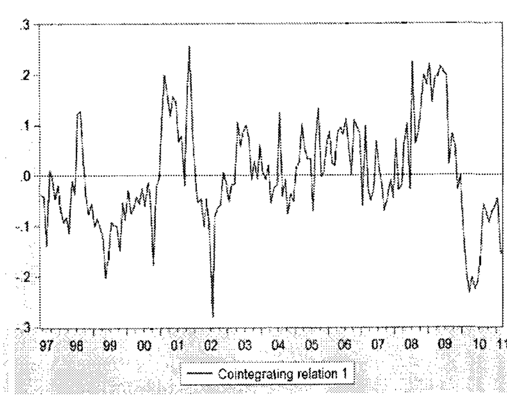
Ontario

Figure 7: Cointegration Space for VAR{EIC,GDP,FCPI,UR} Models



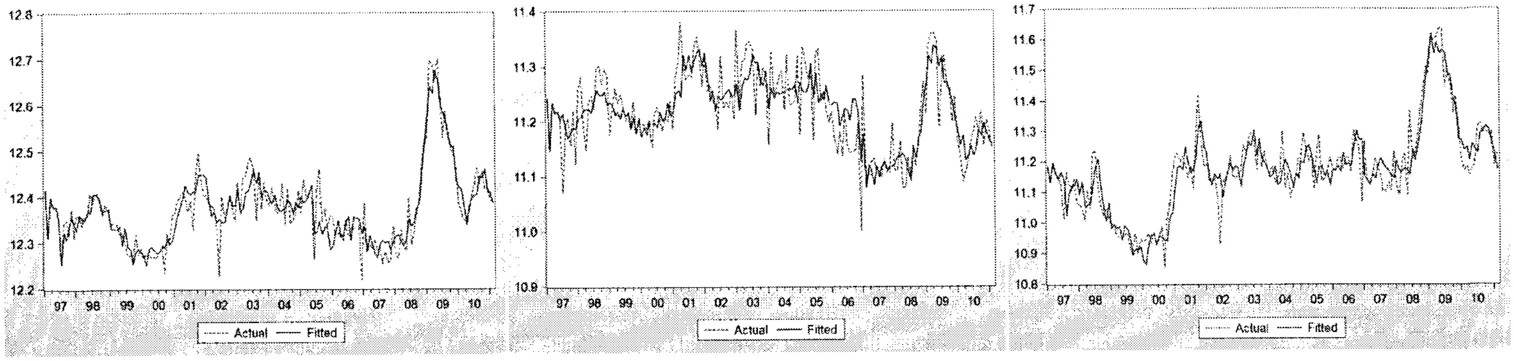


Canada, $r = 2$



Ontario, $r = 1$

Figure 8: Actual/Fitted Log-level EIC from VAR{EIC,GDP,FCPI,UR} Regressions

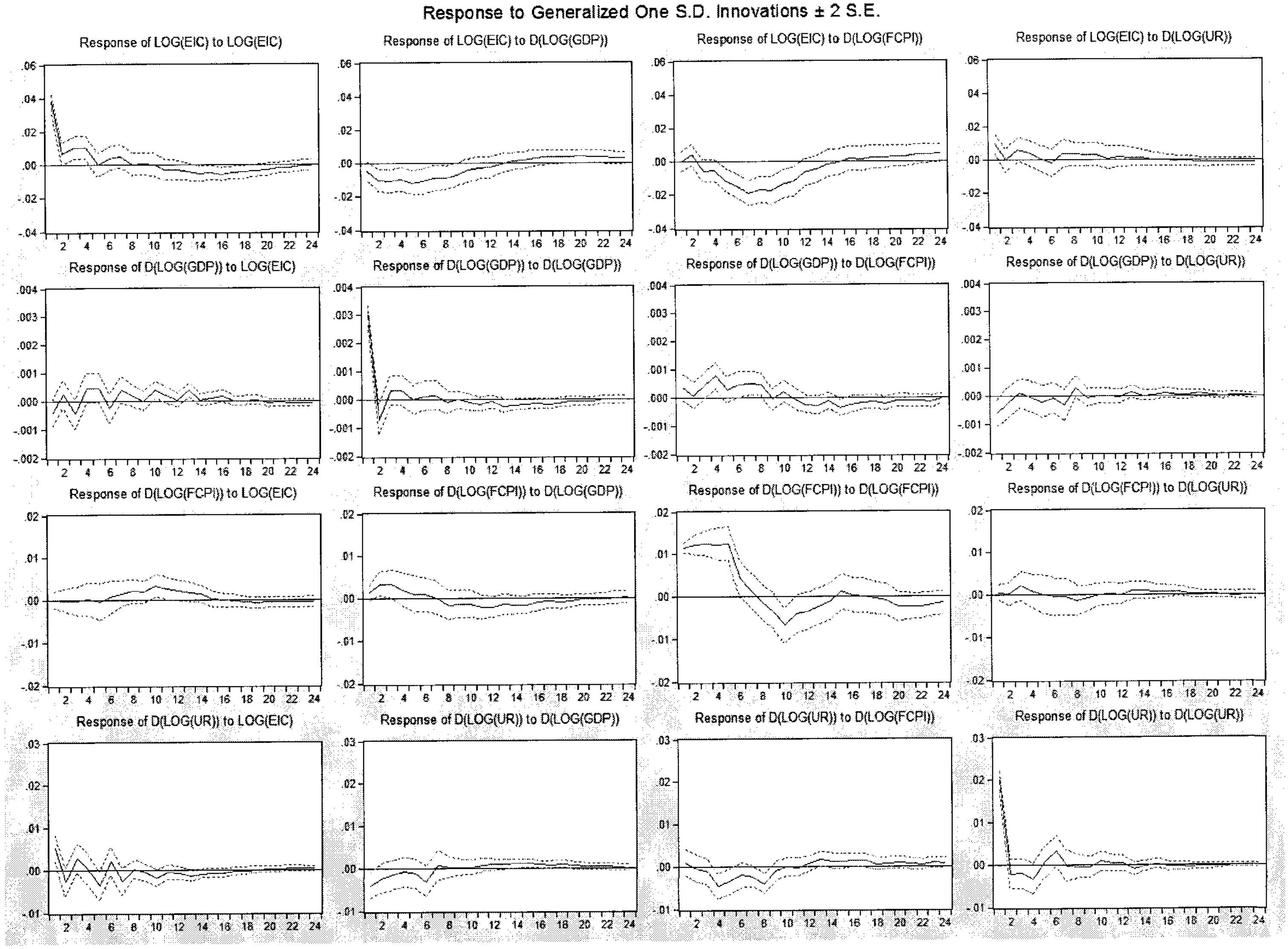


Canada – VAR(6) – with dummies

Quebec – VAR(5) – with dummies

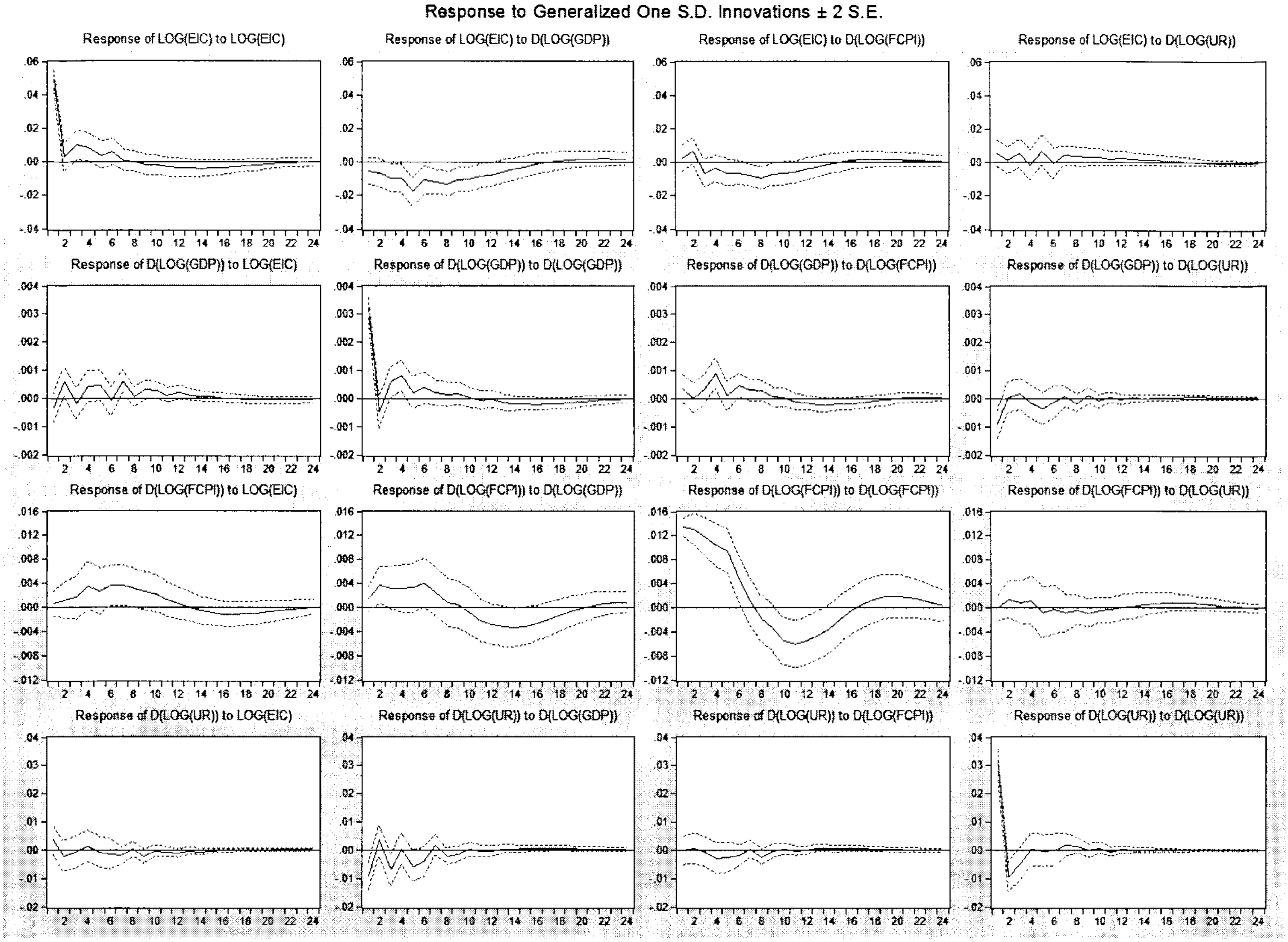
Ontario – VEC(4) – with dummies

Figure 9: Impulse Response Functions from VAR/VEC{EIC,GDP,FCPI,UR} Regressions

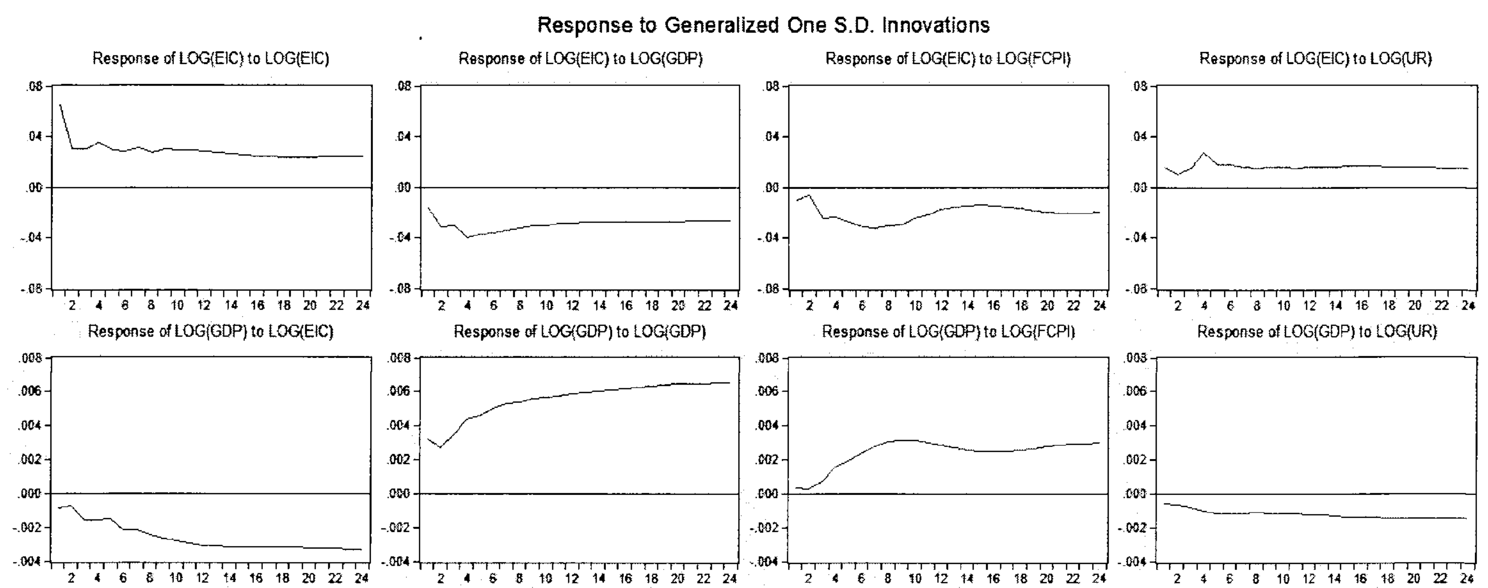


Canada – VAR(5) – with dummies

Figure 9: Impulse Response Functions from VAR/VEC{EIC,GDP,FCPI,UR} Regressions (cont)

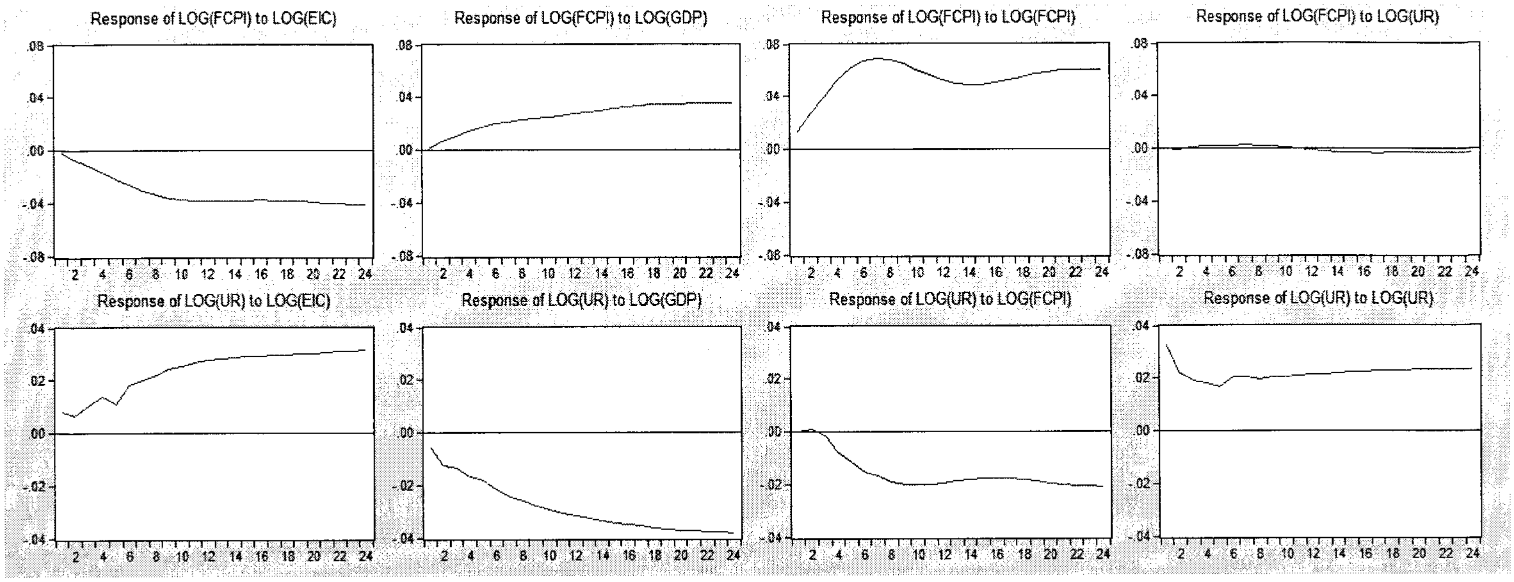


Quebec – VAR(5) – with dummies



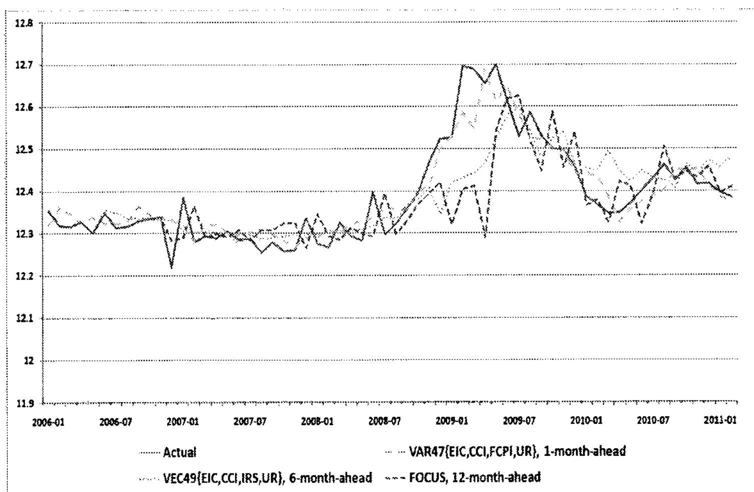
Ontario – VEC(4) – with dummies

Figure 9: Impulse Response Functions from VAR/VEC{EIC,GDP,FCPI,UR} Regressions (cont)

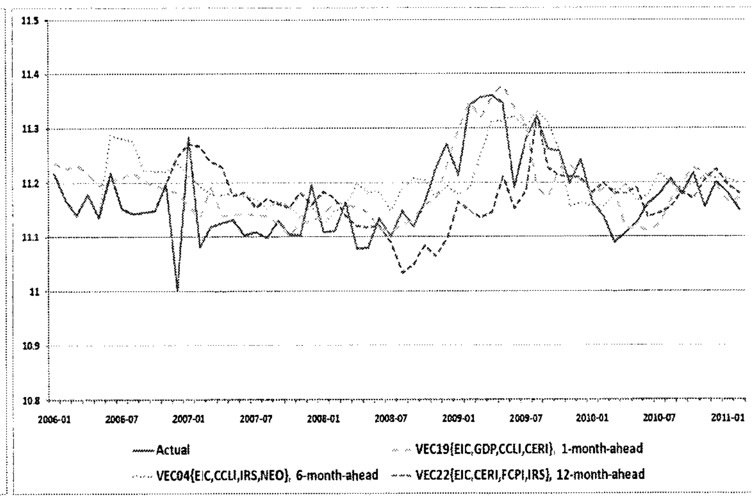


Ontario – VEC(4) – with dummies (cont)

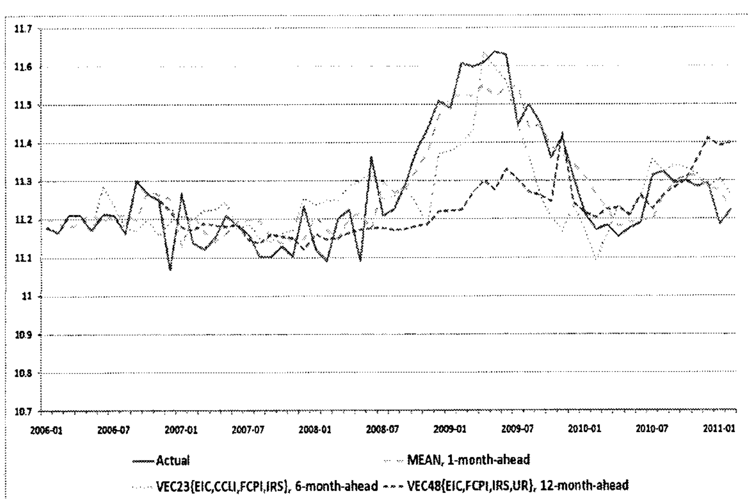
Figure 10: Forecasts of LOG(EIC) from Selected Top-ranked Models



Canada



Quebec



Ontario

Appendix B: Tables

Table 1: VAR/VEC Specifications

$SPEC\ 01: \{EIC, CCLI, FCPI, NEO\}$	$SPEC\ 18: \{EIC, GDP, CCLI, FCPI\}$	$SPEC\ 35: \{EIC, GDP, CCI, FCPI\}$
$SPEC\ 02: \{EIC, CCLI, CERI, NEO\}$	$SPEC\ 19: \{EIC, GDP, CCLI, CERI\}$	$SPEC\ 36: \{EIC, GDP, CCI, CERI\}$
$SPEC\ 03: \{EIC, CCLI, CCI, NEO\}$	$SPEC\ 20: \{EIC, CCLI, CERI, FCPI\}$	$SPEC\ 37: \{EIC, CERI, FCPI, NEO\}$
$SPEC\ 04: \{EIC, CCLI, IRS, NEO\}$	$SPEC\ 21: \{EIC, GDP, CERI, FCPI\}$	$SPEC\ 38: \{EIC, CCI, CERI, NEO\}$
$SPEC\ 05: \{EIC, GDP, FCPI, NEO\}$	$SPEC\ 22: \{EIC, CERI, FCPI, IRS\}$	$SPEC\ 39: \{EIC, CERI, IRS, NEO\}$
$SPEC\ 06: \{EIC, GDP, CERI, NEO\}$	$SPEC\ 23: \{EIC, CCLI, FCPI, IRS\}$	$SPEC\ 40: \{EIC, CCI, FCPI, NEO\}$
$SPEC\ 07: \{EIC, GDP, CCI, NEO\}$	$SPEC\ 24: \{EIC, GDP, FCPI, IRS\}$	$SPEC\ 41: \{EIC, FCPI, IRS, NEO\}$
$SPEC\ 08: \{EIC, GDP, IRS, NEO\}$	$SPEC\ 25: \{EIC, CCLI, CERI, IRS\}$	$SPEC\ 42: \{EIC, CCI, IRS, NEO\}$
$SPEC\ 09: \{EIC, CCLI, FCPI, UR\}$	$SPEC\ 26: \{EIC, GDP, CERI, IRS\}$	$SPEC\ 43: \{EIC, CCLI, GDP, NEO\}$
$SPEC\ 10: \{EIC, CCLI, CERI, UR\}$	$SPEC\ 27: \{EIC, CCLI, CCI, IRS\}$	$SPEC\ 44: \{EIC, CERI, FCPI, UR\}$
$SPEC\ 11: \{EIC, CCLI, CCI, UR\}$	$SPEC\ 28: \{EIC, CCLI, CCI, FCPI\}$	$SPEC\ 45: \{EIC, CCI, CERI, UR\}$
$SPEC\ 12: \{EIC, CCLI, IRS, UR\}$	$SPEC\ 29: \{EIC, CCLI, CCI, CERI\}$	$SPEC\ 46: \{EIC, CERI, IRS, UR\}$
$SPEC\ 13: \{EIC, GDP, FCPI, UR\}$	$SPEC\ 30: \{EIC, CCLI, GDP, CCI\}$	$SPEC\ 47: \{EIC, CCI, FCPI, UR\}$
$SPEC\ 14: \{EIC, GDP, CERI, UR\}$	$SPEC\ 31: \{EIC, CCI, FCPI, IRS\}$	$SPEC\ 48: \{EIC, FCPI, IRS, UR\}$
$SPEC\ 15: \{EIC, GDP, CCI, UR\}$	$SPEC\ 32: \{EIC, CCI, CERI, IRS\}$	$SPEC\ 49: \{EIC, CCI, IRS, UR\}$
$SPEC\ 16: \{EIC, GDP, IRS, UR\}$	$SPEC\ 33: \{EIC, GDP, CCI, IRS\}$	$SPEC\ 50: \{EIC, CCLI, GDP, UR\}$
$SPEC\ 17: \{EIC, GDP, CCLI, IRS\}$	$SPEC\ 34: \{EIC, CCI, CERI, FCPI\}$	

Table 2: Data Sources

Series Name	Data Sources	Series Number	Frequency	Adjustment	Reference Period
EI Program; Canada (CA); Initial and Renewal Claims; Received (EIC)	CANSIM 276-0004	v1992295	Monthly	Seasonally adjusted	1997:01-2011:02
Labour Force Survey (LFS) Estimates; Canada; Unemployment Rates; Both sexes, 15 years and over (UR)	CANSIM 282-0087	v2062815	Monthly	Seasonally adjusted	1976:01-2011:03
Manpower Employment Outlook Survey; Canada (NEO)	Manpower Group		Quarterly	Seasonally adjusted	1992.Q1-2011.Q1
EI Program; Quebec (QC); Initial and Renewal Claims; Received (EIC)	CANSIM 276-0004	v1992300	Monthly	Seasonally adjusted	1997:01-2011:02
LFS Estimates; Quebec; Unemployment Rates; Both sexes, 15 years and over (UR)	CANSIM 282-0087	v2063760	Monthly	Seasonally adjusted	1976:01-2011:03
Manpower Employment Outlook Survey; Quebec (NEO)	Manpower Group		Quarterly	Seasonally adjusted	2004.Q1-2011.Q1
EI Program; Ontario (ON); Initial and Renewal Claims; Received (EIC)	CANSIM 276-0004	v1992301	Monthly	Seasonally adjusted	1997:01-2011:02
LFS Estimates; Ontario; Unemployment Rates; Both sexes, 15 years and over (UR)	CANSIM 282-0087	v2063949	Monthly	Seasonally adjusted	1976:01-2011:03
Manpower Employment Outlook Survey; Ontario (NEO)	Manpower Group		Quarterly	Seasonally adjusted	2004.Q2-2011.Q1
Business leading indicators for Canada; Canada; Composite index of 10 indicators (Index, 1992=100) (CCLI)	CANSIM 377-0003	v7688	Monthly	Smoothed	1952:07-2011:04
Real GDP at Basic Prices; Canada; Chained (2002) dollars; All industries (GDP)	CANSIM 379-0027	v41881175	Monthly	Seasonally adjusted at annually rate	1997:01-2011.02
Government of Canada Marketable Bonds; over 10 years; Average Yield	CANSIM 176-0043	v122487	Monthly	N/A	1936:01-2011:04
Treasury Bill Auction; 3 months; Average Yields	CANSIM 176-0043	v122541	Monthly	N/A	1935:06-2011:04
Fisher Bank of Canada Commodity Price Index; Canada; Total, all commodities (FCPI)	CANSIM 176-0075	v52673496	Monthly	Seasonally unadjusted	1972:01-2011:04
Canadian-Dollar Effective Exchange Rate Index (CERI)	CANSIM 176-0064	v41498903	Monthly	N/A	1996.01-2011:04
Canadian Consumer Confidence Index; Canada (CCI)	Conference Board Canada	CBI	Monthly	Seasonally unadjusted	2001:12-2011:04
Canadian Consumer Confidence Index; Canada (CCI)	Conference Board Canada	CBI	Quarterly	Seasonally unadjusted	1980.Q1-2011.Q1

Table 3: Unit Root Tests (in level)

		Unit Root Tests									Coefficient Estimates			
		None			Constant			Trend			Constant		Trend	
Series	Type	Lags	Test Statistic	p-value	Lags	Test Statistic	p-value	Lags	Test Statistic	p-value	t-statistic	p-value	t-statistic	p-value
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Log EIC (CA)+	ADF	3	-0.0058	0.6794	2	-2.4289	0.1354	2	-2.619	0.2725	2.4291**	0.0162	0.9845	0.3263
	ERS				2	2.5328**		2	8.5842					
Log EIC (QC)+	ADF	2	-0.1211	0.6406	2	-2.7745*	0.0641	2	-2.9808	0.1408	2.7739***	0.0062	-1.1368	0.2573
	ERS				2	2.2948**		2	6.4036*					
Log EIC (ON)	ADF	1	0.0658	0.7024	2	-2.2325	0.1957	2	-3.1158	0.1061	2.2331**	0.0269	2.1524**	0.0328
	ERS				2	2.4311**		2	7.2197					
Log NEO (CA)	ADF	6	0.2005	0.7433	6	-2.4078	0.1412	6	-2.8373	0.1862	2.4094**	0.0172	-1.6268	0.1058
	ERS				6	4.3517		6	12.0369					
Log NEO (QC)	ADF	8	0.0153	0.6862	8	-1.6694	0.4449	9	-3.0786	0.115	1.6696*	0.0971	-2.7104***	0.0075
	ERS				8	5.8549		9	16.7221					
Log NEO (ON)	ADF	9	0.0388	0.6938	8	-1.7984	0.3803	8	-2.6179	0.273	1.7987*	0.0741	-1.9276*	0.0558
	ERS				8	5.0116		8	13.6342					
Log UR (CA)	ADF	1	-0.7222	0.4025	1	-2.2318	0.1959	1	-1.6707	0.7600	2.1920**	0.0298	0.9631	0.3369
	ERS				1	31.3691		1	36.9605					
Log UR (QC)	ADF	1	-1.3051	0.1768	1	-2.5057	0.1159	2	-2.4603	0.3475	2.4346**	0.0160	-1.3224	0.1879
	ERS				1	42.375		2	18.7115					
Log UR (ON)	ADF	1	-0.3853	0.5441	1	-1.9259	0.3198	1	-2.4822	0.3366	1.9040*	0.0587	2.2718**	0.0244
	ERS				1	18.4045		1	41.7255					
Log CCLI	ADF	11	2.3417	0.9955	12	-1.0268	0.743	13	-1.9543	0.6211	1.1604	0.2478	1.7712*	0.0787
	ERS				12	662.5219		13	22.8439					
Log GDP	ADF	4	2.5088	0.9972	3	-2.0991	0.2454	7	-1.6568	0.7658	2.1119**	0.0362	1.0892	0.2778
	ERS				3	533.9383		7	58.3304					
Log IRS	ADF	13	0.5511	0.8342	13	-1.6784	0.4402	13	-1.7748	0.7124	1.6794*	0.0953	0.6891	0.4919
	ERS				13	9.6904		13	21.4546					
Log FCPI	ADF	11	1.1127	0.9308	11	-0.9741	0.7617	9	-2.31	0.4257	1.0360	0.3019	2.2144**	0.0283
	ERS				11	16.9488		9	11.2566					
Log CERI	ADF	11	1.3813	0.9579	12	0.2343	0.974	12	-2.5868	0.2870	-0.1933	0.8470	2.9754***	0.0034
	ERS				12	39.1906		12	32.914					
Log CCI	ADF	13	-0.0643	0.6598	13	-1.7145	0.422	13	-1.7549	0.7218	1.7134*	0.0888	-0.5512	0.5824
	ERS				13	10.5842		13	20.7254					

Notes:

With regard to unit root tests, none, constant, trend respectively represents the three specifications for a unit root test equation: none (i.e. without constant), with a constant and with a linear trend. The lag lengths are determined by the modified information criterion AIC with maximum lag length set to $p_{max} = int\{\min\left[12, \frac{T}{3}\right]\left[\left(\frac{T}{100}\right)^{\frac{1}{4}}\right]\}$., where $int(x)$ denotes the integer part of x and T is the size of the series (see Eviews, 2009, p 391).

The "Lags" columns imply the lag length for the corresponding test equation as selected by the MAIC procedure.

The "Test statistic" columns refer to the ADF's τ-statistic or the ERS' p-statistic. The associated p-values for the ERS tests were not provided. Instead, the critical values at 1%, 5% and 10% for the constant (trend) specifications are given as 1.9236(4.1214), 3.1496(5.6532), 4.2756 (6.8362), respectively, for the full sample 1997.1-2011.02.

With regard to the coefficient estimates, the t-statistics and the associated p-values from the "constant" ("trend") column denotes the standard t-test for the significance of parameter estimates.

***, **, * respectively correspond to the rejection of the null hypothesis that the series in question is a unit root at 1%, 5%, and 10% level of significance.

+ indicates stationarity.

Table 4: Unit Root Tests (in first difference)

		Unit Root Tests									Coefficient Estimates			
		None			Constant			Trend			Constant		Trend	
Series	Type	Lags	Test Statistic	p-value	Lags	Test Statistic	p-value	Lags	Test Statistic	p-value	t-statistic	p-value	t-statistic	p-value
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Log EIC (ON)+	ADF	0	-18.3650***	0	0	-18.3104***	0	0	-18.2553***	0	0.0968	0.9230	0.0297	0.9763
Log NEO (CA)+	ADF	2	-5.2363***	0	2	-5.2179***	0	2	-5.2004***	0.0001	-0.0219	0.9825	-0.2312	0.8175
Log NEO (QC)+	ADF	3	-5.2379***	0	3	-5.2211***	0	3	-5.2022***	0.0001	0.1007	0.9199	-0.2295	0.8188

Log NEO (ON)+	ADF	6	-3.9043***	0.0001	6	-3.8940***	0.0026	6	-3.8986**	0.0142	0.1435	0.8861	-0.3618	0.7180
Series	**Type**	**Lags**	**Test Statistic**	**p-value**	**Lags**	**Test Statistic**	**p-value**	**Lags**	**Test Statistic**	**p-value**	**t-statistic**	**p-value**	**t-statistic**	**p-value**
Log UR (CA)+	ADF	4	-3.9668***	0.0001	4	-3.9614***	0.0021	4	-4.0792***	0.0082	-0.2574	0.7972	0.9883	0.3245
Log UR (QC)+	ADF	0	-15.5050***	0	0	-15.5653***	0	0	-15.5965***	0	-1.1658	0.2454	0.9967	0.3203
Log UR (ON)+	ADF	8	-3.1971***	0.0015	8	-3.1864**	0.0226	8	-3.1879*	0.0906	0.0047	0.9962	0.6307	0.5292
Log CCLI+	ADF	10	-1.5862	0.1059	10	-2.8766**	0.0500	10	-2.797	0.2007	2.3843**	0.0184	-0.2927	0.7702
Log GDP+	ADF	13	-1.6819*	0.0875	3	-3.7220***	0.0046	3	-3.9990**	0.0105	2.5182**	0.0128	-1.4540	0.1479
Log IRS+	ADF	10	-3.2980***	0.0011	10	-3.2940**	0.0168	10	-3.1883*	0.0905	0.4440	0.6577	0.0777	0.9382
Log FCPI+	ADF	5	-3.3481***	0.0009	5	-3.4440**	0.0108	5	-3.4438**	0.0492	0.8444	0.3997	0.2762	0.7827
Log CERI+	ADF	5	-3.4327***	0.0007	5	-3.5690***	0.0074	5	-3.7013**	0.025	0.9876	0.3249	0.9857	0.3258
Log CCI+	ADF	0	-4.1809***	0	0	-4.1684***	0.001	0	-4.1491***	0.0065	0.0747	0.9405	-0.1337	0.8938

Table 5: Residual Diagnostics for ARIMA and VAR/VEC Models

	Dummies?	Region	Model	AICc	BG(12)	JB	BDS(3)	WHITE	RMSE	BIASP	VARP	COVP
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
(A)	No dummies	Canada	ARIMA(2,0,11)	-3.3892	10.0440	4.1011	-1.44E-05	128.1658	0.040557	0.000030	0.051169	0.948801
					(0.6121)	(0.1287)	(0.8940)	(0.2668)				
		Quebec	ARIMA(1,0,11)	-3.0808	17.4241	3.6946	-0.000614	47.86556	0.047681	0.000506	0.093945	0.90555
					(0.1343)	(0.1577)	(0.8468)	(0.8003)				
		Ontario	ARIMA(4,1,4)	-2.4785	10.4781	3.1243	-7.86E-05	59.88269	0.066123	0.001411	0.043915	0.954674
					(0.5741)	(0.2097)	(0.2888)	(0.2708)				
(B)	With dummies	Canada	ARIMA(3,0,11)	-3.4007	4.6114	5.9290*	-4.95E-05	20.2010	0.039425	0.000158	0.023923	0.975918
					(0.9697)	(0.0516)	(0.9624)	(0.2641)				
		Quebec	ARIMA(2,011)	-3.1013	17.1162	1.3992	-0.000657	10.6890	0.046501	0.000654	0.0816	0.917747
					(0.1453)	(0.4968)	(0.8264)	(0.7743)				
		Ontario	ARIMA(5,1,6)	-2.4919	12.7515	4.5502	2.80E-05	18.1993	0.063365	0.001101	0.042388	0.956511
					(0.3874)	(0.1028)	(0.2624)	(0.1979)				
(C)	No dummies	Canada	VAR(5)	-21.6606	15.0446	11.3777	391.0201	0.002064*	0.037949	4.31E-07	0.040713	0.959286
					(0.5214)	(0.1812)	(0.6165)	(0.0772)				
		Quebec	VAR(4)	-20.6713	16.0034	17.1336**	347.4422	0.000929	0.048819		0.132105	0.867871
					(0.4527)	(0.0287)	(0.1398)	(0.1280)				
		Ontario	VAR(4)	-20.0672	24.1194*	14.1571*	373.5784**	4.40E-05	0.064400	2.55E-05	0.003555	0.996420
					(0.0869)	(0.0778)	(0.0209)	(0.3939)				
(D)	With dummies	Canada	VAR(6)	-19.9617	11.3753	13.1217	519.3008	-1.63E-07	0.034718	1.38E-12	0.044936	0.955064
					(0.7858)	(0.1077)	(0.3782)	(0.6892)				
		Quebec	VAR(5)	-19.7951	16.51592	8.7539	428.6143	0.000153*	0.045823	2.06E-11	0.119553	0.880447
					(0.4176)	(0.3635)	(0.3752)	(0.078)				
		Ontario	VAR(4)	-19.8099	22.21682	15.1837*	374.5251*	-6.88E-08	0.063945	1.10E-11	0.000400	0.999600
					(0.1363)	(0.0557)	(0.0956)	(0.6720)				
(E)	With dummies	Ontario	VEC(4)	-19.8879	14.75861	17.8167**	388.4379	-6.88E-08	0.060093	2.27E-12	0.016020	0.983980
					(0.5424)	(0.0226)	(0.1451)	(0.6952)				

Notes:

p-values are in parentheses.

The joint BDS testing is not available for VAR/VEC(s). For the sake of brevity, only the BDS statistics from the equation of concern (i.e. where log EIC is the dependant variable) are displayed. Similarly, the RMSE and its decomposition are presented uniquely for the log EIC equations.

Table 6: AR/MA Structure Diagnostics for ARIMA and VAR/VEC Models

	Canada		Quebec		Ontario	
(A)	ARIMA(2,0,11)	ARIMA(3,0,11) (with dummies)	ARIMA(1,0,11)	ARIMA(2,0,11) (with dummies)	ARIMA(4,1,4)	ARIMA(5,1,6) (with dummies)
	(1)	(2)	(3)	(4)	(5)	(6)
	AR Modulus	**AR Modulus**	**AR Modulus**	**AR Modulus**	**AR Modulus**	**AR Modulus**
	0.529436	0.837059	0.554859	0.468281	0.954135	0.949615
		0.573821			0.861121	0.938198
					0.35149	0.87847

(A)	**MA Modulus**	**MA Modulus**	**MA Modulus**	**MA Modulus**	**MA Modulus**	**MA Modulus**
	0.997261	0.992975	0.999991	0.999999	0.991406	0.991687
	0.995419	0.991883	0.976257	0.990955	0.987526	0.990745
	0.94896	0.932297	0.961805	0.947022	0.204095	0.98823
	0.936692	0.916212	0.953488	0.945168		0.181708
	0.932334	0.873194	0.917647	0.941803		
(B)	**VAR(5)**	**VAR(6) (with dummies)**	**VAR(4)**	**VAR(5) (with dummies)**	**VAR(4)**	**VAR(4) (with dummies)**
	AR Modulus	**AR Modulus**	**AR Modulus**	**AR Modulus**	**AR Modulus**	**AR Modulus**
	0.914765	0.938129	0.878045	0.897663	0.880396	0.883154
	0.914765	0.938129	0.878045	0.897663	0.880396	0.883154
	0.912012	0.909966	0.863884	0.882607	0.791791	0.744710
	0.912012	0.909966	0.863884	0.882607	0.755260	0.734338
	0.795794	0.904595	0.740395	0.735727	0.706749	0.705004

Table 7: Chow Tests for Structural Breaks in Parameters of ARIMA and VAR/VEC Models

	Canada				**Quebec**				**Ontario**			
	Dependant Variable	**Date**	**F-statistic**	**p-value**	**Dependant Variable**	**Date**	**F-statistic**	**p-value**	**Dependant Variable**	**Date**	**F-statistic**	**p-value**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**
(A)	**ARIMA(2,0,11)**				**ARIMA(1,0,11)**				**ARIMA(4,1,4)**			
	Log EIC	2005-07	1.5386**	0.0295	Log EIC	2005-06	1.5908**	0.0203	D(Log EIC)	2001-11	2.3159***	0.0011
		2008-10	1.6106**	0.0385						2008-05	1.5382**	0.0468
(B)	**VAR(5)**				**VAR(4)**				**VAR(4)**			
	Log EIC	2005-06	1.5146**	0.0402	Log EIC	2006-12	1.5548**	0.0316	D(Log EIC)	2005-02	1.5491**	0.0335
		2002-06	1.9585**	0.0102								
	Log FCPI	2008-06	1.7931**	0.0131	D(Log FCPI)	2008-08	1.7882**	0.0142	D(Log FCPI)	2008-08	1.8513**	0.0105

Table 8: Johansen's Cointegration Tests for VAR{EIC,GDP,FCPI,UR} Models

	Cointegration Tests						**Tests for Restrictions on the β vector**		
	Canada		**Quebec**		**Ontario**			**Canada**	**Quebec**
Cointegration Rank	**Eigenvalue**	**Max-Eigen Statistic**	**Eigenvalue**	**Max-Eigen Statistic**	**Eigenvalue**	**Max-Eigen Statistic**	**Restrictions**	**F-Statistics**	**F-Statistics**
(1)	**(2)**	**(3)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**
$r = 0$	0.249372	46.75569**	0.192830	35.13232**	0.225501	42.16400**			
$r = 1$	0.134459	23.53736**	0.153779	27.38390**	0.142037	25.27699**	$\beta(1,1) = 0$ $\beta(2,1) = 0$ $\beta(3,1) = 0$ $\beta(4,1) = 0$	4.7616 (0.1901)	10.6274** (0.0139)
$r = 2$	0.065005	10.95598	0.092825	15.97680**	0.136581	24.23114**	$\beta(1,1) = 0$ $\beta(2,1) = 0$ $\beta(3,1) = 0$ $\beta(4,1) = 0$	4.5061 (0.1050)	8.9675** (0.0113)
$r = 3$	0.012237	2.006857	0.036610	6.116642**	0.023264	3.883955**	$\beta(1,1) = 0$ $\beta(2,1) = 0$ $\beta(3,1) = 0$ $\beta(4,1) = 0$	0.2586 (0.6111)	6.9001*** (0.0086)

Notes:

The default 0.05 critical values (without exogenous variables) are respectively 27.58434, 21.13162, 14.2646, 3.841466 for $r = 0$, $r = 1$, $r = 2$, and $r = 3$. These critical values indicate a full rank cointegration space (i.e. r=4) for Quebec and Ontario. This implies that these VARs are stationary in levels, thus, clearly contradicts the results from unit root tests presented in Table 3

p-values of the F-statistics are in parentheses.

For cointegration tests, ** indicates that the null of r cointegration relations is rejected and the alternative of cointegration rank equal to $r + 1$ is accepted at 5% according to the default critical values.

For cointegration restriction tests, *, **, *** imply the (joint) significance of the β-coefficients listed in column 9 at 10%, 5%, and 1%.

Table 9: Cointegration Space Diagnostics for VEC{EIC,GDP,FCPI,UR} Models

Canada				Quebec			Ontario					
$r=0$	$r=2$			$r=0$	$r=1$		$r=0$	$r=1$		$r=2$		
AR Roots	AR Roots	t-stat (α_1)	t-stat (α_2)	AR Roots	AR Roots	t-stat (α_1)	AR Roots	AR Roots	t-stat (α_1)	AR Roots	t-stat (α_1)	t-stat (α_2)
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
0.938129	1.000000	-5.28422***	-0.90202	0.8977	1.000000	-4.51039***	0.8832	1.0000	-4.0685***	1.0000	-4.2379***	0.1093
0.938129	1.000000	3.68244***	-1.27211	0.8977	1.000000	0.86227	0.8832	1.0000	-0.1334	1.0000	-0.0988	0.5969
0.909966	0.921678	1.87594*	-2.37514**	0.8827	1.000000	3.04173***	0.7447	1.0000	-2.7387***	0.9107	-2.6557**	5.2262***
0.909966	0.921678	-1.29402	3.01515***	0.8827	0.903699	-1.23441	0.7343	0.8922	2.4276**	0.9107	2.4576**	-0.5917
0.904595	0.906539			0.7357	0.903699		0.7050	0.8922		0.8832		

Table 10: Estimation of Cointegration Space and Adjustment Space for Ontario VEC{EIC,GDP,FCPI,UR}

β' Vector				α Vector			
Independent Variables				Dependent Variables			
Log(EIC)	Log(GDP)	Log(FCPI)	Log(UR)	D(Log(EIC))	D(Log(GDP))	D(Log(FCPI))	D(Log(UR))
(2)	(3)	(4)	(5)				
1.000000	-0.798375***	0.110514	-0.684234***	-0.364102***	-0.000590	-0.050513***	0.110175**
	[-3.29317]	[1.19877]	[-5.95195]	[-4.06854]	[-0.13336]	[-2.73872]	[2.42760]

Notes:

t-statistics are in square brackets.

Table 11: Short-run Granger Causality Tests for VAR/VEC{EIC,GDP,FCPI,UR} Models

	Canada - VAR(6)					Quebec - VAR(5)					Ontario - VEC(4)				
DVs	Regressors					Regressors					Regressors				
	EIC	GDP	FCPI	UR	ALL	EIC	GDP	FCPI	UR	ALL	EIC	GDP	FCPI	UR	ALL
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
EIC	N/A	20.66***	20.62***	6.52	72.67***	N/A	17.58***	7.184	1.76	40.19***	N/A	25.87***	16.32***	6.03	53.70***
		(0.0021)	(0.0021)	(0.3671)	(0)		(0.0035)	(0.2073)	(0.8815)	(0.0004)		(0)	(0.0026)	(0.1966)	(0)
GDP	30.96***	N/A	26.06***	9.17	60.64***	10.98**	N/A	15.12***	5.22	33.47***	13.71***	N/A	16.10***	1.41	29.90***
	(0)		(0.0002)	(0.1643)	(0)	(0.05)		(0.0099)	(0.3893)	(0.004)	(0.0083)		(0.0029)	(0.8418)	(0.0029)
FCPI	13.63**	7.93	N/A	10.63	29.39**	8.2078	13.01**	N/A	6.77	23.045*	14.55***	9.94**	N/A	8.36*	27.29***
	(0.0341)	(0.2431)		(0.1003)	(0.0438)	(0.1451)	(0.0233)		(0.2383)	(0.0832)	(0.0057)	(0.0415)		(0.0791)	(0.007)
UR	15.62**	9.72	15.43**	N/A	63.95***	1.7755	22.37***	2.98	N/A	32.60***	11.20***	11.76**	8.16*	N/A	33.06***
	(0.016)	(0.1368)	(0.0172)		(0)	(0.8792)	(0.0004)	(0.7033)		(0.0053)	(0.0244)	(0.0192)	(0.0858)		(0.0009)

Notes:

Column 1 (DVs) list the dependant variables of the test equations in reduced forms.

Row 3 contains labels for columns 2 to 16 where EIC, GDP, FCPI, and UR denote the regressors of the test equations, and ALL represents the joint test of significance.

Each cell contains the F statistic and the associated p-value indicating whether the lags of the respective regressor or of all regressors significantly enter the test equations.

Variables enter the test regressions in log-level if stationary (like log EIC in Canada and Quebec), otherwise, in log-first-difference.

Table 12: In-sample Fit Comparison between ARIMA and VAR/VEC{EIC,GDP,FCPI,UR} Models

	ARIMA						VAR/VEC{EIC,GDP,FCPI,UR}					
Region	Model	LOGL	RMSE	BIASP	VARP	COVP	Model	LOGL	RMSE	BIASP	VARP	COVP
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Canada	ARIMA(3,0,11)	303.0084	0.039425	0.000158	0.023923	0.975918	VAR(6)	316.4756	0.034718	1.38E-12	0.044936	0.955064
Quebec	ARIMA(2,011)	274.4135	0.046501	0.000654	0.0816	0.917747	VAR(5)	272.9008	0.045823	2.06E-11	0.119553	0.880447
Ontario	ARIMA(5,1,6)	219.7454	0.063365	0.001101	0.042388	0.956511	VEC(4)	228.4974	0.060093	2.27E-12	0.016020	0.983980

Table 13: Cholesky Variance Decomposition in VAR/VEC{EIC,GDP,FCPI,UR} Models

	Canada – VAR(6)					Quebec – VAR(5)					Ontario – VEC(4)				
Variable	Period	Variance Decomposition				Period	Variance Decomposition				Period	Variance Decomposition			
		EIC	GDP	FCPI	UR		EIC	GDP	FCPI	UR		EIC	GDP	FCPI	UR
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
EIC	1	100.00	0.00	0.00	0.00	1	100	0	0	0	1	100.00	0.00	0.00	0.00
		(100.00 100.00)	(0.00 0.00)	(0.00 0.00)	(0.00 0.00)		(100 100)	(0 0)	(0 0)	(0 0)					
	3	86.20	9.86	2.76	1.17	3	92.43	4.14	3.16	0.27	6	59.88	26.29	10.90	2.93
		(76.09 96.32)	(0.80 18.93)	(-1.24 6.76)	(-2.58 4.93)		(84.32 100.54)	(-2.03 10.30)	(-2.28 8.59)	(-2.36 2.90)					
	6	65.32	19.11	14.11	1.47	6	76.81	17.40	4.27	1.52	12	53.64	28.01	15.72	2.62
		(51.84 78.80)	(6.04 32.18)	(4.19 24.02)	(-2.82 5.75)		(64.22 89.39)	(5.55 29.26)	(-1.50 10.03)	(-2.98 6.03)					
	12	42.35	17.67	37.89	2.09	12	61.28	29.30	8.19	1.24	24	51.35	30.71	14.40	3.54
		(27.08 57.63)	(2.94 32.41)	(17.97 57.80)	(-3.27 7.44)		(43.62 78.94)	(12.07 46.52)	(-1.50 17.87)	(-2.82 5.30)					
GDP	1	1.72	98.28	0.00	0.00	1	1.15	98.85	0.00	0.00	1	6.90	93.10	0.00	0.00
		(-2.56 6.01)	(93.99 102.56)	(0.00 0.00)	(0.00 0.00)		(-2.49 4.78)	(95.22 102.49)	(0.00 0.00)	(0.00 0.00)					
	3	4.09	91.28	1.93	2.70	3	4.63	93.28	0.84	1.25	6	12.91	80.84	6.02	0.23
		(-2.80 10.97)	(82.07 100.49)	(-2.07 5.94)	(-2.63 8.02)		(-2.19 11.45)	(84.73 101.84)	(-2.54 4.22)	(-3.05 5.54)					
	6	7.72	80.06	8.69	3.54	6	6.80	84.89	6.34	1.98	12	17.32	71.69	10.92	0.08
		(-0.86 16.29)	(68.99 91.12)	(1.38 16.01)	(-2.47 9.55)		(-0.64 14.24)	(74.48 95.29)	(-0.49 13.17)	(-3.02 6.97)					
	12	9.76	72.66	12.14	5.44	12	10.50	80.19	7.02	2.28	24	20.56	70.81	8.59	0.03
		(0.67 18.85)	(60.53 84.79)	(2.90 21.38)	(-1.49 12.37)		(0.88 20.12)	(67.91 92.48)	(-0.51 14.56)	(-2.96 7.52)					
FCPI	1	0.00	1.46	98.54	0.00	1	0.23	1.25	98.52	0.00	1	2.49	0.57	96.93	0.00
		(-1.64 1.64)	(-2.37 5.28)	(94.38 102.70)	(0.00 0.00)		(-2.01 2.47)	(-2.30 4.81)	(94.36 102.68)	(0.00 0.00)					
	3	0.02	5.37	93.70	0.90	3	0.85	5.55	92.33	1.26	6	11.19	3.63	84.21	0.96
		(-2.71 2.76)	(-3.52 14.26)	(84.04 103.37)	(-1.98 3.78)		(-3.51 5.22)	(-3.26 14.36)	(82.21 102.46)	(-2.26 4.79)					
	6	0.11	3.86	95.36	0.67	6	4.86	9.38	84.52	1.23	12	21.83	4.56	71.89	1.72
		(-4.58 4.80)	(-5.35 13.07)	(84.16 106.56)	(-3.74 5.07)		(-5.45 15.17)	(-4.49 23.26)	(67.41 101.64)	(-3.49 5.95)					
	12	3.58	4.52	90.45	1.45	12	7.94	10.02	80.66	1.38	24	28.66	9.14	60.64	1.56
		(-3.97 11.13)	(-5.17 14.22)	(76.65 104.24)	(-5.07 7.97)		(-5.12 21.00)	(-4.46 24.50)	(60.35 100.96)	(-3.39 6.15)					
UR	1	6.60	2.84	0.42	90.14	1	1.18	7.62	0.04	91.16	1	6.36	1.26	0.18	92.19
		(-0.79 13.99)	(-2.07 7.75)	(-2.11 2.94)	(81.55 98.73)		(-2.61 4.96)	(-0.01 15.24)	(-1.62 1.70)	(82.87 99.46)					
	3	9.61	4.60	0.72	85.06	3	1.44	11.69	0.04	86.83	6	20.22	23.09	5.25	51.44
		(0.75 18.47)	(-1.73 10.94)	(-2.71 4.16)	(74.70 95.43)		(-3.34 6.23)	(2.38 20.99)	(-2.71 2.80)	(76.75 96.90)					
	6	11.42	6.32	7.16	75.11	6	1.78	14.98	1.18	82.06	12	33.90	31.00	10.50	24.60
		(2.91 19.93)	(-0.23 12.86)	(0.88 13.43)	(64.30 85.93)		(-3.66 7.21)	(5.86 24.10)	(-3.02 5.38)	(71.55 92.57)					
	12	12.75	6.03	11.13	70.10	12	2.57	15.34	1.55	80.54	24	41.42	39.48	8.05	11.05
		(4.02 21.47)	(-0.46 12.52)	(3.08 19.18)	(58.62 81.57)		(-3.01 8.14)	(6.07 24.61)	(-2.93 6.04)	(69.18 91.90)					

Notes:

Row 3 contains labels for columns 3 to 6, 8 to 11, and 13 to 16 where EIC, GDP, FCPI, and UR denote the contributors to the forecast error variance of the variable indicated by the row label.

The +/-2 standard error bands, only available for VARs, are shown in brackets.

The decomposition is orthogonalized by the Cholesky method, which is invariant to the ordering of variables as long as the residual correlations are below 0.2 (see Quan and Huyghebaert, 2004). Even though some correlation coefficients of the three VAR/VEC(s) lie between 0.2 and 0.3, these results are not substantially altered if the ordering is reversed.

Table 14: Forecasting the EIC Claims in Canada

Canada	Model	Information Set	RMSE	Rank	MAE	Rank	U-Theil	Rank	CI	Rank	DA	Rank	DM	HLN
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
One-month-ahead														
Benchmark	ARIMA	EIC	0.052278	48	0.040421	51	0.970204	48	0.645161	30	0.331946	28		
Top	MEDIAN	ALL	0.04421	2	0.033215	3	0.820458	2	0.66129	20	0.343392	17	1.850818*	2.846259***
Winners	VAR47	EIC,CCI,FCPI,UR	0.043822	1	0.032923	1	0.813274	1	0.725806	3	0.369407	4	1.394775	3.017729***
	VAR21	EIC,GDP,CERI,FCPI	0.047741	22	0.036731	22	0.886	22	0.677419	15	0.348075	15	0.991356	2.666721***
	VAR35	EIC,GDP,CCI,FCPI	0.047562	19	0.036227	17	0.882682	19	0.693548	11	0.359521	11	0.863111	2.563644**
	VEC17	EIC,GDP,CCLI,IRS	0.046935	11	0.035822	14	0.871048	11	0.709677	5	0.371488	3	1.000923	2.324089**
Strict	VEC23	EIC,CCLI,FCPI,IRS	0.04705	13	0.036306	18	0.87317	13	0.725806	3	0.394381	1	0.83236	2.136379**
Winners	MRBEST	ANY	0.047172	14	0.03689	23	0.87543	14	0.677419	15	0.33871	21	1.181905	3.142393***
	VAR06	EIC,GDP,CERI,NEO	0.045912	5	0.035138	10	0.852061	5	0.693548	11	0.359521	11	1.22889	2.886489***
	VAR13	EIC,GDP,FCPI,UR	0.048494	30	0.038904	40	0.899981	30	0.66129	20	0.351717	12	0.854247	2.613503**
	VAR14	EIC,GDP,CERI,UR	0.047859	24	0.038123	31	0.888184	24	0.66129	20	0.343392	17	0.857236	2.435295**
	VAR28	EIC,CCLI,CCI,FCPI	0.047329	16	0.03701	25	0.878347	16	0.66129	20	0.337149	22	0.851484	2.306713**
	VAR36	EIC,GDP,CCI,CERI	0.047202	15	0.037249	26	0.875992	15	0.693548	11	0.359521	11	1.043781	2.640780**
	VAR40	EIC,CCI,FCPI,NEO	0.046716	8	0.034956	9	0.866968	8	0.693548	11	0.359521	11	0.792713	2.817362***
	VEC24	EIC,GDP,FCPI,IRS	0.046781	9	0.035238	12	0.868176	9	0.693548	11	0.367846	5	0.919799	2.048073**
	VEC25	EIC,CCLI,CERI,IRS	0.04671	7	0.034601	8	0.866861	7	0.693548	11	0.349116	13	1.031898	3.092616***
	VEC26	EIC,GDP,CERI,IRS	0.047498	18	0.03343	5	0.881491	18	0.677419	15	0.33975	18	1.113437	2.596158**
	VEC31	EIC,CCI,FCPI,IRS	0.048142	27	0.0355	13	0.89343	27	0.677419	15	0.389698	2	0.685495	2.523691**
	VEC32	EIC,CCI,CERI,IRS	0.045983	6	0.033558	6	0.853367	6	0.725806	3	0.363163	7	1.707918*	3.752295***
	VEC33	EIC,GDP,CCI,IRS	0.050412	38	0.034394	7	0.935569	38	0.709677	5	0.364204	6	0.333788	3.029407***
	VAR07	EIC,GDP,CCI,NEO	0.049486	34	0.038375	36	0.918382	34	0.645161	27	0.348595	14	0.581907	2.999630***
Weak	VAR18	EIC,GDP,CCLI,FCPI	0.047705	21	0.037772	29	0.885324	21	0.645161	27	0.33923	20	0.795819	2.174497**
Winners	VAR19	EIC,GDP,CCLI,CERI	0.047615	20	0.038255	33	0.883662	20	0.645161	27	0.33923	20	0.765674	2.365587**
	VAR29	EIC,CCLI,CCI,CERI	0.047991	25	0.038613	38	0.890639	25	0.645161	27	0.331946	25	0.836983	2.616683**
	DMSE	ALL	0.044411	3	0.033214	2	0.824201	3	0.629032	33	0.32102	34	1.926283*	2.866410***
	MEAN	ALL	0.0445	4	0.033326	4	0.825859	4	0.612903	41	0.315817	39	2.062440**	2.850200***
	VAR01	EIC,CCLI,FCPI,NEO	0.049888	36	0.038822	39	0.925845	36	0.548387	55	0.278356	54	0.39291	2.280940**
	VAR02	EIC,CCLI,CERI,NEO	0.049779	35	0.038938	41	0.923815	35	0.532258	56	0.26847	56	0.513495	2.602928**
	VAR03	EIC,CCLI,CCI,NEO	0.048849	31	0.037739	27	0.906556	31	0.580645	50	0.294485	47	0.76057	3.103144***
	VAR05	EIC,GDP,FCPI,NEO	0.047413	17	0.035998	15	0.879917	17	0.596774	44	0.311134	41	0.803127	2.359471**
	VAR08	EIC,GDP,IRS,NEO	0.050598	40	0.037743	28	0.939017	40	0.612903	41	0.323101	32	0.453228	2.591025**
	VAR09	EIC,CCLI,FCPI,UR	0.049145	32	0.039098	42	0.912062	32	0.612903	41	0.315817	39	0.582265	2.464535**
	VAR11	EIC,CCLI,CCI,UR	0.051093	44	0.040093	49	0.948206	44	0.612903	41	0.310614	44	0.379731	2.955083***
	VAR15	EIC,GDP,CCI,UR	0.047796	23	0.039173	43	0.887011	23	0.629032	33	0.327263	28	1.012937	3.006342***
	VAR20	EIC,CCLI,CERI,FCPI	0.048431	28	0.039474	46	0.898802	28	0.612903	41	0.315817	39	0.69868	2.463729**
	VAR27	EIC,CCLI,CCI,IRS	0.050901	41	0.04139	54	0.944644	41	0.645161	27	0.326743	29	0.233055	2.175773**
Mixed	VAR30	EIC,CCLI,GDP,CCI	0.047021	12	0.03835	35	0.872633	12	0.629032	33	0.335588	23	1.032736	2.459101**
Models	VAR34	EIC,CCI,CERI,FCPI	0.046824	10	0.035163	11	0.868981	10	0.612903	41	0.323101	32	1.787632*	2.950044***
	VAR37	EIC,CERI,FCPI,NEO	0.051222	45	0.036973	24	0.950593	45	0.564516	52	0.282518	53	0.36459	2.775010***
	VAR38	EIC,CCI,CERI,NEO	0.053093	51	0.038345	34	0.985328	51	0.580645	50	0.290323	51	-0.239758	3.177612***
	VAR39	EIC,CERI,IRS,NEO	0.055625	55	0.04012	50	1.032312	55	0.548387	55	0.275234	55	-0.640664	2.242897**
	VAR41	EIC,FCPI,IRS,NEO	0.054779	54	0.036586	21	1.01661	54	0.596774	44	0.300728	46	-0.497753	1.893130*
	VAR43	EIC,CCLI,GDP,NEO	0.048475	29	0.037838	30	0.899615	29	0.580645	50	0.316337	36	0.757129	2.467275**
	VAR44	EIC,CERI,FCPI,UR	0.049902	37	0.038414	37	0.926099	37	0.629032	33	0.314776	40	0.746053	2.716278***
	VAR45	EIC,CCI,CERI,UR	0.048126	26	0.036586	21	0.893133	26	0.645161	27	0.323621	30	1.442826	3.404993***
	VAR48	EIC,FCPI,IRS,UR	0.052681	49	0.039444	45	0.977677	49	0.612903	41	0.310614	44	-0.118568	1.953470*
	VAR50	EIC,CCLI,GDP,UR	0.049486	34	0.040151	51	0.918381	33	0.629032	33	0.327263	28	0.62745	2.472482**
	VEC04	EIC,CCLI,IRS,NEO	0.0518	46	0.038197	32	0.961329	46	0.580645	50	0.291363	49	0.280691	2.941211***
	VEC10	EIC,CCLI,CERI,UR	0.051064	42	0.040455	53	0.94767	42	0.596774	44	0.319459	35	0.274589	2.494445**
	VEC22	EIC,CERI,FCPI,IRS	0.051066	43	0.036171	16	0.947709	43	0.612903	41	0.310614	44	0.298566	3.427782***
	VEC42	EIC,CCI,IRS,NEO	0.050552	39	0.036344	19	0.938163	39	0.66129	20	0.330905	26	0.576821	3.871842***
	VEC46	EIC,CERI,IRS,UR	0.054121	52	0.039687	47	1.004396	52	0.564516	52	0.284599	52	-0.581612	2.812665***
	VEC49	EIC,CCI,IRS,UR	0.052428	48	0.039349	44	0.972975	48	0.580645	50	0.306972	45	-0.035027	2.802902***
Strict	FOCUS	ANY	0.054632	53	0.039852	48	1.013888	53	0.580645	50	0.291363	49	-0.486555	1.837653*
Losers	VAR12	EIC,CCLI,IRS,UR	0.052829	50	0.041537	55	0.980423	50	0.629032	33	0.32102	34	-0.141192	2.333448**
	VAR16	EIC,GDP,IRS,UR	0.059686	56	0.044682	56	1.107673	56	0.548387	55	0.290843	50	-1.482717	0.740262
Six-months-ahead														
Benchmark	ARIMA	EIC	0.107688	41	0.074307	27	0.874639	41	0.666667	35	0.341644	39		
Top Winners	VEC49	EIC,CCI,IRS,UR	0.079579	2	0.053754	2	0.646337	2	0.842105	1	0.429363	2	1.366846	2.734181***
	VAR21	EIC,GDP,CERI,FCPI	0.100598	19	0.071288	21	0.817054	19	0.684211	25	0.374269	17	0.935861	2.096179**
	VAR35	EIC,GDP,CCI,FCPI	0.103456	28	0.074147	27	0.840268	28	0.684211	25	0.374269	17	0.392086	2.322741**
	VAR47	EIC,CCI,FCPI,UR	0.100987	20	0.070969	19	0.820211	20	0.701754	18	0.377039	14	0.582335	2.571626**
	VEC17	EIC,GDP,CCLI,IRS	0.098939	15	0.069323	13	0.803577	15	0.719298	11	0.405663	6	1.13495	2.949452***
Strictly	VEC23	EIC,CCLI,FCPI,IRS	0.085729	5	0.062654	5	0.696285	5	0.754386	6	0.423207	4	1.06986	2.048997**
Winners	DMSE	ALL	0.094301	8	0.065278	7	0.765911	8	0.684211	25	0.374269	17	1.557006	2.438962**

Table 14: Forecasting the EIC Claims in Canada (cont)

(1)	Model (2)	Information Set (3)	RMSE (4)	Rank (5)	MAE (6)	Rank (7)	U-Theil (8)	Rank (9)	CI (10)	Rank (11)	DA (12)	Rank (13)	DM (14)	HLN (15)
Six-months-ahead														
Strict Winners	FOCUS	ANY	0.077257	1	0.052544	1	0.627479	1	0.754386	6	0.378578	13	1.351068	2.380610**
	MRBEST	ANY	0.084645	4	0.060173	3	0.687482	4	0.754386	6	0.382579	12	1.107263	2.646385**
	VAR15	EIC,GDP,CCI,UR	0.101072	21	0.070285	16	0.8209	21	0.701754	18	0.366882	21	1.148512	2.249801**
	VAR29	EIC,CCLI,CCI,CERI	0.103631	29	0.072564	23	0.841691	29	0.719298	11	0.371499	18	0.636388	2.161780**
	VAR30	EIC,CCLI,GDP,CCI	0.101155	22	0.073973	26	0.821576	22	0.684211	25	0.362881	23	0.716464	2.046614**
	VAR34	EIC,CCI,CERI,FCPI	0.10145	25	0.072852	24	0.82397	25	0.736842	8	0.384426	10	0.451243	2.305998**
	VAR45	EIC,CCI,CERI,UR	0.100108	16	0.070704	18	0.813073	16	0.701754	18	0.366882	21	0.915531	2.723940***
	VEC22	EIC,CERI,FCPI,IRS	0.097894	14	0.067197	10	0.795092	14	0.701754	18	0.357649	27	0.469082	2.278537**
	VEC24	EIC,GDP,FCPI,IRS	0.091856	7	0.071072	20	0.746054	7	0.701754	18	0.389658	9	0.80534	2.164442**
	VEC25	EIC,CCLI,CERI,IRS	0.095359	11	0.064427	6	0.774506	11	0.754386	6	0.382579	12	0.987227	2.843885***
	VEC31	EIC,CCI,FCPI,IRS	0.080908	3	0.06621	9	0.657133	3	0.684211	25	0.423207	4	0.859526	1.993062*
	VEC32	EIC,CCI,CERI,IRS	0.103793	30	0.069921	15	0.843003	30	0.684211	25	0.353955	30	0.917853	2.631921**
	VEC33	EIC,GDP,CCI,IRS	0.087474	6	0.061289	4	0.710464	6	0.754386	6	0.43952	1	1.236122	2.613220**
Weak Winners	VAR11	EIC,CCLI,CCI,UR	0.100482	17	0.072239	22	0.816115	17	0.666667	34	0.349338	35	0.922143	2.144920**
	VAR20	EIC,CCLI,CERI,FCPI	0.096443	12	0.069498	14	0.783306	12	0.666667	34	0.359495	26	1.148661	2.194034**
	VAR36	EIC,GDP,CCI,CERI	0.105886	37	0.074389	29	0.860006	37	0.666667	34	0.349338	35	0.258123	2.084763**
	VEC26	EIC,GDP,CERI,IRS	0.095187	10	0.067447	11	0.773108	10	0.666667	34	0.359495	26	1.334491	2.483697**
Mixed Models	MEAN	ALL	0.094983	9	0.065959	8	0.77145	9	0.649123	39	0.356725	29	1.556174	2.389274**
	MEDIAN	ALL	0.097365	13	0.067767	12	0.790799	13	0.649123	39	0.345337	37	1.494233	2.321021**
	VAR02	EIC,CCLI,CERI,NEO	0.101373	23	0.07363	25	0.823348	23	0.614035	48	0.327793	45	0.439103	1.873437*
	VAR03	EIC,CCLI,CCI,NEO	0.104106	31	0.077556	38	0.845547	31	0.578947	54	0.29486	55	0.264667	1.970908*
	VAR05	EIC,GDP,FCPI,NEO	0.111805	50	0.08251	50	0.908079	50	0.666667	34	0.349338	35	-0.490262	1.848633*
	VAR07	EIC,GDP,CCI,NEO	0.107039	39	0.080612	47	0.869368	39	0.596491	51	0.314251	49	0.048478	2.123239**
	VAR09	EIC,CCLI,FCPI,UR	0.105765	35	0.075455	33	0.859019	35	0.614035	48	0.318867	47	0.307235	1.572133
	VAR13	EIC,GDP,FCPI,UR	0.106223	38	0.075548	34	0.862736	38	0.631579	44	0.331794	44	0.244418	1.599948
	VAR18	EIC,GDP,CCLI,FCPI	0.103394	27	0.074855	31	0.83976	27	0.666667	34	0.349338	35	0.558828	1.983242*
	VAR19	EIC,GDP,CCLI,CERI	0.108478	45	0.078945	43	0.881052	45	0.684211	25	0.362881	23	-0.107428	1.668274
	VAR27	EIC,CCLI,CCI,IRS	0.104497	32	0.077741	39	0.848721	32	0.719298	11	0.391813	7	0.385533	1.934787*
	VAR28	EIC,CCLI,CCI,FCPI	0.104941	33	0.077085	37	0.852326	33	0.649123	39	0.345337	37	0.306095	2.223033**
	VAR37	EIC,CERI,FCPI,NEO	0.105862	36	0.079146	44	0.859806	36	0.631579	44	0.331794	44	0.140617	2.166070**
	VAR38	EIC,CCI,CERI,NEO	0.108738	46	0.082029	48	0.883163	46	0.649123	39	0.356725	29	-0.052842	2.267847**
	VAR40	EIC,CCI,FCPI,NEO	0.100536	18	0.076128	35	0.816548	18	0.666667	34	0.359495	26	0.348301	2.171253**
	VAR44	EIC,CERI,FCPI,UR	0.101375	24	0.070596	17	0.823362	24	0.649123	39	0.336411	39	1.215	2.059617**
	VAR50	EIC,CCLI,GDP,UR	0.107988	42	0.078412	40	0.877071	42	0.666667	34	0.349338	35	-0.035628	1.789261*
	VEC04	EIC,CCLI,IRS,NEO	0.105155	34	0.076216	36	0.854067	34	0.736842	8	0.407202	5	0.336133	2.688723***
	VEC10	EIC,CCLI,CERI,UR	0.102602	26	0.075406	32	0.833329	26	0.701754	18	0.389658	9	0.505637	2.056972**
	VEC42	EIC,CCI,IRS,NEO	0.108193	44	0.078445	41	0.878742	44	0.701754	18	0.366882	21	-0.171749	2.368515**
Strict Losers	VAR01	EIC,CCLI,FCPI,NEO	0.107812	41	0.079828	45	0.875647	41	0.614035	48	0.318867	47	-0.013634	1.707677*
	VAR06	EIC,GDP,CERI,NEO	0.111153	49	0.083125	51	0.902782	49	0.631579	44	0.331794	44	-0.326753	2.007977**
	VAR08	EIC,GDP,IRS,NEO	0.121474	55	0.091508	56	0.98661	55	0.54386	56	0.304094	53	-1.162416	1.570408
	VAR12	EIC,CCLI,IRS,UR	0.110397	47	0.082141	49	0.896641	47	0.578947	54	0.310249	51	-0.377587	1.731147*
	VAR14	EIC,GDP,CERI,UR	0.108101	43	0.074594	30	0.877994	43	0.631579	44	0.331794	44	-0.073506	1.357352
	VAR39	EIC,CERI,IRS,NEO	0.120223	54	0.091141	55	0.976447	54	0.561404	55	0.296707	54	-1.326265	1.796610*
	VAR41	EIC,FCPI,IRS,NEO	0.12489	56	0.090604	54	1.014351	56	0.631579	44	0.331794	44	-1.103684	1.20936
	VAR43	EIC,CCLI,GDP,NEO	0.110634	48	0.083179	52	0.898565	48	0.596491	51	0.306556	52	-0.249197	1.711115*
	VAR48	EIC,FCPI,IRS,UR	0.113849	51	0.080112	46	0.924677	51	0.614035	48	0.312404	50	-0.638648	0.828761
	VEC16	EIC,GDP,IRS,UR	0.119377	53	0.084364	53	0.969576	53	0.596491	51	0.314251	49	-1.068827	1.263506
	VEC46	EIC,CERI,IRS,UR	0.114595	52	0.078867	42	0.930738	52	0.578947	54	0.290859	56	-0.693462	0.992414
Twelve-months-ahead														
Benchmark	ARIMA	EIC	0.145221	49	0.112679	54	0.811361	49	0.647059	54	0.327566	56		
Top Winners	FOCUS	ANY	0.099487	1	0.066812	1	0.555843	1	0.823529	1	0.412918	2	1.288729	2.464316**
Strict Winners	VAR21	EIC,GDP,CERI,FCPI	0.136367	28	0.104633	34	0.761891	28	0.666667	40	0.340254	40	0.912906	2.018903**
	VAR35	EIC,GDP,CCI,FCPI	0.136321	26	0.101889	21	0.761638	26	0.647059	54	0.334102	48	0.903722	2.084590**
	VAR47	EIC,CCI,FCPI,UR	0.141061	43	0.104015	30	0.788121	43	0.686275	26	0.363322	19	0.347346	1.526371
	VEC17	EIC,GDP,CCLI,IRS	0.136112	25	0.105241	38	0.760469	25	0.705882	12	0.39331	9	0.582868	2.793804***
	VEC23	EIC,CCLI,FCPI,IRS	0.124761	2	0.092024	4	0.69705	2	0.784314	3	0.418301	1	1.177058	2.748067***
	DMSE	ALL	0.129534	4	0.090885	2	0.723716	4	0.72549	9	0.395617	7	1.27157	2.653797**
	MEAN	ALL	0.130151	5	0.09141	3	0.727165	5	0.72549	9	0.395617	7	1.225615	2.564299**
	MEDIAN	ALL	0.132554	11	0.09583	9	0.74059	11	0.666667	40	0.348328	32	1.163182	2.416376**
	VAR02	EIC,CCLI,CERI,NEO	0.135583	20	0.104974	37	0.757511	20	0.686275	26	0.363322	19	0.867864	2.252192**
	VAR03	EIC,CCLI,CCI,NEO	0.135648	21	0.10339	26	0.757873	21	0.666667	40	0.348328	32	0.717388	2.083125**
	VAR06	EIC,GDP,CERI,NEO	0.130818	6	0.095669	8	0.730891	6	0.686275	26	0.35371	27	1.416281	2.325708**
	VAR07	EIC,GDP,CCI,NEO	0.136354	27	0.104198	31	0.761818	27	0.686275	26	0.35371	27	0.561331	1.764766*
	VAR11	EIC,CCLI,CCI,UR	0.133689	16	0.103049	25	0.746933	16	0.666667	40	0.348328	32	1.21167	2.393306**
	VAR12	EIC,CCLI,IRS,UR	0.140936	42	0.111286	52	0.787419	42	0.666667	40	0.348328	32	0.566631	1.862092*
	VAR13	EIC,GDP,FCPI,UR	0.138086	33	0.104375	32	0.771499	33	0.686275	26	0.363322	19	0.686907	1.937819*
	VAR14	EIC,GDP,CERI,UR	0.139847	40	0.105738	39	0.781334	40	0.666667	40	0.340254	40	0.675953	1.808523*

Table 14: Forecasting the EIC Claims in Canada (cont)

(1)	Model (2)	Information Set (3)	RMSE (4)	Rank (5)	MAE (6)	Rank (7)	U-Theil (8)	Rank (9)	CI (10)	Rank (11)	DA (12)	Rank (13)	DM (14)	HLN (15)
Twelve-months-ahead														
	VAR15	EIC,GDP,CCI,UR	0.131337	7	0.096486	10	0.733789	7	0.686275	26	0.35371	27	1.329983	2.465949**
	VAR29	EIC,CCLI,CCI,CERI	0.135387	19	0.104694	35	0.756419	19	0.686275	26	0.35371	27	1.035637	2.378479**
	VAR30	EIC,CCLI,GDP,CCI	0.131521	8	0.103033	24	0.734816	8	0.686275	26	0.363322	19	1.256718	2.398820**
	VAR36	EIC,GDP,CCI,CERI	0.132625	12	0.101759	20	0.740985	12	0.666667	40	0.340254	40	1.147627	2.560021**
	VAR37	EIC,CERI,FCPI,NEO	0.14067	41	0.09977	15	0.785937	41	0.686275	26	0.347174	33	0.263356	1.552379
	VAR39	EIC,CERI,IRS,NEO	0.143371	46	0.101734	19	0.801024	46	0.666667	40	0.340254	40	0.10537	1.510972
	VAR43	EIC,CCLI,GDP,NEO	0.137388	31	0.107625	45	0.767597	31	0.705882	12	0.367935	13	0.713692	2.053771**
Strict	VAR44	EIC,CERI,FCPI,UR	0.138469	34	0.099017	13	0.773638	34	0.686275	26	0.363322	19	0.598008	1.772678*
Winners	VAR45	EIC,CCI,CERI,UR	0.135772	22	0.102665	22	0.758569	22	0.666667	40	0.335256	41	0.804737	2.499371**
	VAR48	EIC,FCPI,IRS,UR	0.145214	48	0.106729	42	0.811321	48	0.647059	54	0.334102	48	0.000659	1.170277
	VEC16	EIC,GDP,IRS,UR	0.142843	45	0.108071	46	0.798072	45	0.72549	9	0.366782	14	0.21526	2.102583**
	VEC22	EIC,CERI,FCPI,IRS	0.13156	9	0.096683	11	0.735033	9	0.666667	40	0.356401	21	0.529187	2.874525***
	VEC26	EIC,GDP,CERI,IRS	0.139791	39	0.102924	23	0.781021	39	0.666667	40	0.348328	32	0.370019	2.133617**
	VEC42	EIC,CCI,IRS,NEO	0.143606	47	0.103563	27	0.802338	47	0.705882	12	0.39331	9	0.122725	1.639883
	VEC46	EIC,CERI,IRS,UR	0.137644	32	0.097518	12	0.769027	32	0.686275	26	0.35371	27	0.725521	2.301749**
	VEC49	EIC,CCI,IRS,UR	0.131905	10	0.092026	5	0.736965	10	0.784314	3	0.399077	4	0.629504	2.071097**
	VAR01	EIC,CCLI,FCPI,NEO	0.132875	14	0.103746	29	0.742382	14	0.647059	54	0.334102	48	1.029047	2.318450**
	VAR05	EIC,GDP,FCPI,NEO	0.138919	35	0.104848	36	0.776152	35	0.647059	54	0.327566	56	0.605649	1.766723*
	VAR08	EIC,GDP,IRS,NEO	0.139582	38	0.104508	33	0.779857	38	0.647059	54	0.334102	48	0.444237	1.752879*
	VAR09	EIC,CCLI,FCPI,UR	0.135912	23	0.107589	44	0.759352	23	0.647059	54	0.334102	48	0.79147	1.871492*
Weak	VAR20	EIC,CCLI,CERI,FCPI	0.1361	24	0.108853	47	0.760402	24	0.647059	54	0.327566	56	0.775715	1.920804*
Winners	VAR27	EIC,CCLI,CCI,IRS	0.139107	36	0.10899	48	0.777203	36	0.647059	54	0.334102	48	0.62239	1.768678*
	VAR28	EIC,CCLI,CCI,FCPI	0.132788	13	0.103678	28	0.741899	13	0.647059	54	0.334102	48	0.668715	1.67072
	VAR34	EIC,CCI,CERI,FCPI	0.136763	29	0.101309	18	0.764103	29	0.647059	54	0.327566	56	0.760368	2.256029**
	VAR41	EIC,FCPI,IRS,NEO	0.15172	54	0.111259	51	0.847672	54	0.647059	54	0.327566	56	-0.40437	1.127763
	VEC24	EIC,GDP,FCPI,IRS	0.124906	3	0.093748	6	0.697858	3	0.647059	54	0.343714	34	0.905866	2.661710**
	MRBEST	ANY	0.16389	55	0.116391	56	0.915665	55	0.745098	6	0.377932	11	-0.447421	2.849675***
	VAR18	EIC,GDP,CCLI,FCPI	0.134766	18	0.106305	41	0.75295	18	0.647059	54	0.327566	56	0.870592	1.895191*
	VAR19	EIC,GDP,CCLI,CERI	0.133923	17	0.106944	43	0.748238	17	0.666667	40	0.340254	40	0.859131	2.093764**
	VAR38	EIC,CCI,CERI,NEO	0.13319	15	0.093955	7	0.744142	15	0.627451	56	0.32872	50	0.655422	2.091619**
	VAR40	EIC,CCI,FCPI,NEO	0.139307	37	0.100954	17	0.77832	37	0.627451	56	0.32872	50	0.408118	1.696538*
Mixed	VAR50	EIC,CCLI,GDP,UR	0.141344	44	0.115295	55	0.789701	44	0.686275	26	0.35371	27	0.397555	1.836742*
Models	VEC04	EIC,CCLI,IRS,NEO	0.136843	30	0.100568	16	0.764552	30	0.745098	6	0.398693	5	0.75996	2.458843**
	VEC10	EIC,CCLI,CERI,UR	0.148882	53	0.110197	49	0.831816	53	0.666667	40	0.340254	40	-0.241356	1.475668
	VEC25	EIC,CCLI,CERI,IRS	0.148214	52	0.099119	14	0.828082	52	0.745098	6	0.377932	11	-0.100906	1.24216
	VEC31	EIC,CCI,FCPI,IRS	0.145936	50	0.110346	50	0.815354	50	0.666667	40	0.373702	12	-0.032854	1.555248
	VEC32	EIC,CCI,CERI,IRS	0.164552	56	0.112497	53	0.919367	56	0.686275	26	0.360631	20	-0.646709	0.809848
	VEC33	EIC,GDP,CCI,IRS	0.14692	51	0.106206	40	0.820851	51	0.686275	26	0.410611	3	-0.031476	2.079079**

Table 15: Forecasting EI Claims in Quebec

(1)	Model (2)	Information Set (3)	RMSE (4)	Rank (5)	MAE (6)	Rank (7)	U-Theil (8)	Rank (9)	CI (10)	Rank (11)	DA (12)	Rank (13)	DM (14)	HLN (15)
One-month-ahead														
Benchmark	ARIMA	EIC	0.068503	56	0.052802	54	0.971532	56	0.66129	45	0.333247	54		
Top	VEC19	EIC,GDP,CCLI,CERI	0.057434	6	0.043721	5	0.81455	6	0.725806	11	0.385796	11	3.591073***	4.028454***
Winners	VEC18	EIC,GDP,CCLI,FCPI	0.057644	8	0.044581	9	0.817532	8	0.725806	11	0.396722	5	2.848562***	4.788984***
	FOCUS	ANY	0.05794	11	0.044607	10	0.821729	11	0.693548	27	0.354058	41	2.060006**	3.451170***
	VAR20	EIC,CCLI,CERI,FCPI	0.062982	39	0.048797	38	0.893232	39	0.725806	11	0.385796	11	2.077653**	3.459938***
	VAR29	EIC,CCLI,CCI,CERI	0.064776	49	0.051226	50	0.91868	49	0.693548	27	0.369667	31	1.707718*	3.242293***
	VAR34	EIC,CCI,CERI,FCPI	0.063992	44	0.048674	36	0.907553	44	0.725806	11	0.376951	25	0.830605	2.998442***
	VAR37	EIC,CERI,FCPI,NEO	0.059674	18	0.043958	6	0.846314	18	0.693548	27	0.369667	31	2.114778**	3.945836***
	VAR38	EIC,CCI,CERI,NEO	0.063212	41	0.048996	41	0.896499	41	0.693548	27	0.360822	37	0.373144	3.198694***
	VAR40	EIC,CCI,FCPI,NEO	0.059499	16	0.042759	2	0.84384	16	0.725806	11	0.385796	11	9.298301***	4.162252***
	VEC08	EIC,GDP,IRS,NEO	0.061035	29	0.047944	29	0.865625	29	0.693548	27	0.380593	15	1.768842*	3.954444***
	VEC14	EIC,GDP,CERI,UR	0.05757	7	0.043209	4	0.81647	7	0.693548	27	0.346774	44	2.506421**	3.798544***
	VEC16	EIC,GDP,IRS,UR	0.064285	47	0.051355	51	0.911717	47	0.693548	27	0.408689	3	0.81949	3.234914***
	VEC22	EIC,CERI,FCPI,IRS	0.055317	1	0.044641	11	0.784526	1	0.693548	27	0.354058	41	3.772450***	5.280762***
	VEC23	EIC,CCLI,FCPI,IRS	0.063686	42	0.04971	45	0.903221	42	0.709677	16	0.425078	2	0.775387	3.154049***
	VEC24	EIC,GDP,FCPI,IRS	0.060808	26	0.047495	23	0.862399	26	0.709677	16	0.394901	6	1.550225	3.330504***
	VEC41	EIC,FCPI,IRS,NEO	0.060345	22	0.047856	27	0.855828	22	0.741935	2	0.399063	4	2.920104***	4.314886***
Strict	VEC42	EIC,CCI,IRS,NEO	0.059938	21	0.047052	17	0.850067	21	0.677419	37	0.378772	19	1.742267*	3.461798***
Winners	DMSE	ALL	0.057363	5	0.04436	8	0.813536	5	0.725806	11	0.376951	25	2.752377***	3.675865***
	MEAN	ALL	0.05774	9	0.0449	12	0.818882	9	0.725806	11	0.376951	25	2.707322***	3.787646***
	MEDIAN	ALL	0.057844	10	0.044967	13	0.820356	10	0.677419	37	0.366805	33	2.852994***	3.824267***

Table 15: Forecasting EI Claims in Quebec (cont)

	Model	Information Set	RMSE	Rank	MAE	Rank	U-Theil	Rank	CI	Rank	DA	Rank	DM	HLN
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
One-month-ahead														
Strict Winners	MRBEST	ANY	0.05958	17	0.047243	21	0.844988	17	0.741935	2	0.381374	13	1.949392*	3.498370***
	VAR01	EIC,CCLI,FCPI,NEO	0.062246	34	0.047141	19	0.882796	34	0.693548	27	0.380593	15	1.31141	3.513162***
	VAR02	EIC,CCLI,CERI,NEO	0.061799	31	0.047722	26	0.876455	31	0.693548	27	0.369667	31	2.332517**	3.514814***
	VAR09	EIC,CCLI,FCPI,UR	0.064203	45	0.052597	53	0.91055	45	0.677419	37	0.39282	7	1.012411	3.527428***
	VAR30	EIC,CCLI,GDP,CCI	0.062658	35	0.048691	37	0.888643	35	0.677419	37	0.378772	19	1.706685*	3.358088***
	VAR31	EIC,CCI,FCPI,IRS	0.061835	32	0.047154	20	0.87696	32	0.725806	11	0.376951	25	1.304198	3.122116***
	VAR35	EIC,GDP,CCI,FCPI	0.068102	55	0.050138	47	0.965838	55	0.677419	37	0.378772	19	0.068721	2.314246**
	VAR36	EIC,GDP,CCI,CERI	0.062984	40	0.049076	42	0.893256	40	0.677419	37	0.35692	39	1.287224	3.397934***
	VAR38	EIC,CCLI,CCI,FCPI	0.066677	52	0.050849	49	0.945638	52	0.677419	37	0.378772	19	1.084637	2.709365***
	VAR44	EIC,CERI,FCPI,UR	0.059198	15	0.047409	22	0.839561	15	0.709677	16	0.382934	12	3.682145***	4.959969***
	VAR49	EIC,CCI,IRS,UR	0.062051	33	0.04885	39	0.880021	33	0.677419	37	0.366805	33	1.173205	3.171470***
	VEC06	EIC,GDP,CERI,NEO	0.057149	4	0.043202	3	0.810507	4	0.677419	37	0.343392	51	3.051490***	3.784523***
	VEC17	EIC,GDP,CCLI,IRS	0.058863	14	0.04673	16	0.83482	14	0.709677	16	0.425078	2	2.337713**	4.646506***
	VEC26	EIC,GDP,CERI,IRS	0.059719	19	0.046145	14	0.846952	19	0.677419	37	0.35692	39	1.974548*	3.449751***
	VEC39	EIC,CERI,IRS,NEO	0.05687	3	0.044296	7	0.806551	3	0.709677	16	0.365245	34	2.843786***	3.986370***
	VEC46	EIC,CERI,IRS,UR	0.056794	2	0.042619	1	0.805472	2	0.725806	11	0.370187	27	2.406385**	3.886152***
	VEC50	EIC,CCLI,GDP,UR	0.059807	20	0.046482	15	0.8482	20	0.693548	27	0.369667	31	10.634415***	4.274401***
Weak Winners	VAR10	EIC,CCLI,CERI,UR	0.060869	27	0.049113	43	0.863267	27	0.66129	45	0.344693	50	4.008659***	4.337148***
	VAR25	EIC,CCLI,CERI,IRS	0.064264	46	0.050291	48	0.91141	46	0.66129	45	0.353538	43	1.298048	3.193144***
	VAR32	EIC,CCI,CERI,IRS	0.060354	23	0.048902	40	0.855957	23	0.66129	45	0.353538	43	1.850458*	3.575825***
	VAR45	EIC,CCI,CERI,UR	0.058353	12	0.047511	24	0.827583	12	0.66129	45	0.344693	50	2.549327**	4.192005***
	VAR47	EIC,CCI,FCPI,UR	0.060965	28	0.048511	34	0.864631	28	0.66129	45	0.377471	21	1.810427*	3.806472***
	VEC04	EIC,CCLI,IRS,NEO	0.058812	13	0.047124	18	0.834094	13	0.66129	45	0.377471	21	2.700726***	4.417702***
Mixed Models	VAR03	EIC,CCLI,CCI,NEO	0.062872	36	0.04817	30	0.891664	36	0.629032	51	0.361342	36	1.369918	3.138492***
	VAR05	EIC,GDP,FCPI,NEO	0.064287	48	0.048474	33	0.911738	48	0.645161	48	0.376691	26	0.74332	3.412793***
	VAR07	EIC,GDP,CCI,NEO	0.064941	50	0.048469	32	0.921012	50	0.612903	54	0.346514	47	0.596096	2.891695***
	VAR11	EIC,CCLI,CCI,UR	0.061561	30	0.048367	31	0.873083	30	0.629032	51	0.337409	53	1.680146*	3.554712***
	VAR13	EIC,GDP,FCPI,UR	0.062952	38	0.049605	44	0.892805	38	0.612903	54	0.346514	47	1.433074	3.507388***
	VAR15	EIC,GDP,CCI,UR	0.060728	24	0.047895	28	0.86126	24	0.629032	51	0.337409	53	2.018013**	3.473433***
	VAR27	EIC,CCLI,CCI,IRS	0.06288	37	0.048643	35	0.891779	37	0.612903	54	0.346514	47	1.039544	2.970912***
	VAR33	EIC,GDP,CCI,IRS	0.066912	53	0.052228	52	0.948963	53	0.596774	56	0.32128	56	0.257009	2.446302**
	VAR43	EIC,CCLI,GDP,NEO	0.063801	43	0.050028	46	0.904851	43	0.596774	56	0.345213	48	0.972955	3.339669***
	VAR48	EIC,FCPI,IRS,UR	0.067667	54	0.053182	55	0.95968	54	0.645161	48	0.362643	35	0.112744	2.402439**
	VEC12	EIC,CCLI,IRS,UR	0.06648	51	0.053507	56	0.942838	51	0.66129	45	0.39256	8	0.444277	3.059720***
	VEC21	EIC,GDP,CERI,FCPI	0.060745	25	0.047583	25	0.861506	25	0.645161	48	0.323621	55	2.078516**	3.397732***
Six-months-ahead														
Benchmark	ARIMA	EIC	0.101485	56	0.087756	56	1.033293	56	0.561404	56	0.338873	53		
Top Winners	VEC04	EIC,CCLI,IRS,NEO	0.072216	3	0.057879	4	0.735287	3	0.736842	4	0.426593	22	2.995102***	4.453894***
Strict Winners	FOCUS	ANY	0.077872	9	0.060482	6	0.792868	9	0.719298	15	0.373653	50	1.892377*	3.918016***
	VAR20	EIC,CCLI,CERI,FCPI	0.090746	29	0.075221	29	0.923953	29	0.701754	22	0.427208	16	1.471698	2.449488**
	VAR29	EIC,CCLI,CCI,CERI	0.094612	40	0.078916	39	0.963314	40	0.701754	22	0.427208	16	1.056402	2.386598**
	VAR34	EIC,CCI,CERI,FCPI	0.087513	21	0.073887	25	0.891032	21	0.684211	33	0.409049	35	1.704182*	5.241421***
	VAR37	EIC,CERI,FCPI,NEO	0.088157	23	0.072721	21	0.897585	23	0.666667	42	0.409665	29	2.217456**	5.918243***
	VAR38	EIC,CCI,CERI,NEO	0.09094	30	0.07577	31	0.925921	30	0.631579	49	0.392121	41	0.158319	5.240017***
	VAR40	EIC,CCI,FCPI,NEO	0.089653	26	0.075103	28	0.912821	26	0.666667	42	0.409665	29	1.861528*	5.144788***
	VEC08	EIC,GDP,IRS,NEO	0.079116	12	0.065102	12	0.805536	12	0.736842	4	0.426593	22	2.468798**	4.325111***
	VEC14	EIC,GDP,CERI,UR	0.079038	11	0.063806	10	0.804744	11	0.719298	15	0.366574	51	2.826630***	4.121398***
	VEC16	EIC,GDP,IRS,UR	0.090499	28	0.072711	20	0.92143	28	0.701754	22	0.427208	16	1.221057	3.559107***
	VEC18	EIC,GDP,CCLI,FCPI	0.091968	31	0.074171	26	0.936389	31	0.684211	33	0.392121	41	0.996381	2.535148**
	VEC22	EIC,CERI,FCPI,IRS	0.065944	1	0.052046	1	0.671422	1	0.736842	4	0.378578	48	3.692032***	5.700630***
	VEC23	EIC,CCLI,FCPI,IRS	0.071474	2	0.056902	2	0.727724	2	0.719298	15	0.426593	22	2.974627***	4.287978***
	VEC24	EIC,GDP,FCPI,IRS	0.082025	15	0.067453	16	0.835158	15	0.719298	15	0.445983	4	1.680104*	3.562114***
	VEC41	EIC,FCPI,IRS,NEO	0.076804	5	0.06311	7	0.781997	5	0.701754	22	0.409049	35	2.399289**	5.082631***
	VEC42	EIC,CCI,IRS,NEO	0.087904	22	0.073482	24	0.895014	22	0.666667	42	0.391505	45	1.775702*	3.728507***
	DMSE	ALL	0.083228	16	0.069434	18	0.847405	16	0.719298	15	0.426593	22	3.427324***	4.362139***
	MEAN	ALL	0.08447	19	0.070927	19	0.860051	19	0.719298	15	0.426593	22	3.089222***	4.135369***
	MEDIAN	ALL	0.087111	20	0.072853	23	0.886939	20	0.719298	15	0.426593	22	2.658562**	3.863786***
	MRBEST	ANY	0.07462	4	0.057278	3	0.759761	4	0.736842	4	0.378578	48	2.911856***	5.064321***
	VAR01	EIC,CCLI,FCPI,NEO	0.096371	47	0.080702	48	0.981217	47	0.684211	33	0.409049	35	0.748402	2.570647**
	VAR02	EIC,CCLI,CERI,NEO	0.094379	39	0.079911	42	0.960941	39	0.631579	49	0.392121	41	1.211467	2.711606***
	VAR03	EIC,CCLI,CCI,NEO	0.094269	38	0.079229	40	0.959818	38	0.684211	33	0.42844	12	1.500408	2.689230***
	VAR05	EIC,GDP,FCPI,NEO	0.09348	34	0.077953	33	0.951787	34	0.719298	15	0.445983	4	1.206788	3.004601***
	VAR07	EIC,GDP,CCI,NEO	0.092872	32	0.077972	34	0.945593	32	0.701754	22	0.427208	16	1.43088	3.377438***
	VAR09	EIC,CCLI,FCPI,UR	0.100711	55	0.086142	55	1.025407	55	0.701754	22	0.409049	35	0.090215	1.939404*
	VAR10	EIC,CCLI,CERI,UR	0.096834	49	0.081748	51	0.985935	49	0.614035	53	0.393352	37	0.679131	2.320369**
	VAR11	EIC,CCLI,CCI,UR	0.093994	37	0.080288	44	0.957014	37	0.684211	33	0.42844	12	0.930607	2.274699**
	VAR13	EIC,GDP,FCPI,UR	0.099378	52	0.083219	52	1.011841	52	0.684211	33	0.409049	35	0.244023	2.453909**

Table 15: Forecasting EI Claims in Quebec (cont)

(1)	Model (2)	Information Set (3)	RMSE (4)	Rank (5)	MAE (6)	Rank (7)	U-Theil (8)	Rank (9)	CI (10)	Rank (11)	DA (12)	Rank (13)	DM (14)	HLN (15)
Six-months-ahead														
	VAR15	EIC,GDP,CCI,UR	0.093669	35	0.078471	37	0.953706	35	0.701754	22	0.44783	2	1.115388	2.836937***
	VAR25	EIC,CCLI,CERI,IRS	0.094862	41	0.078624	38	0.965857	41	0.596491	54	0.395199	36	0.891438	2.257285**
	VAR27	EIC,CCLI,CCI,IRS	0.096203	46	0.079774	41	0.979509	46	0.666667	42	0.409665	29	0.652318	1.861408*
	VAR30	EIC,CCLI,GDP,CCI	0.09779	51	0.081574	50	0.995672	51	0.666667	42	0.430286	7	0.575416	1.956091*
	VAR31	EIC,CCI,FCPI,IRS	0.095344	42	0.080781	49	0.970761	42	0.649123	46	0.391505	45	0.827032	3.056539***
	VAR32	EIC,CCI,CERI,IRS	0.092988	33	0.076597	32	0.946773	33	0.578947	55	0.339489	52	1.147265	4.019939***
	VAR33	EIC,GDP,CCI,IRS	0.095807	45	0.08048	46	0.97548	45	0.684211	33	0.42844	12	0.791602	2.297676**
	VAR35	EIC,GDP,CCI,FCPI	0.095737	44	0.080024	43	0.974766	44	0.684211	33	0.409049	35	0.664634	3.386443***
	VAR36	EIC,GDP,CCI,CERI	0.096808	48	0.080542	47	0.985671	48	0.666667	42	0.409665	29	0.601045	2.629114**
	VAR38	EIC,CCLI,CCI,FCPI	0.100185	53	0.085146	54	1.020058	53	0.649123	46	0.391505	45	1.344191	1.955943*
	VAR43	EIC,CCLI,GDP,NEO	0.100561	54	0.085021	53	1.023886	54	0.614035	53	0.466297	1	0.14215	1.812953*
Strict	VAR44	EIC,CERI,FCPI,UR	0.080842	13	0.068349	17	0.82311	13	0.684211	33	0.42844	12	2.656673**	4.065280***
Winners	VAR45	EIC,CCI,CERI,UR	0.090108	27	0.074921	27	0.91745	27	0.614035	53	0.373961	49	1.483159	4.549042***
	VAR47	EIC,CCI,FCPI,UR	0.09391	36	0.078356	36	0.956168	36	0.666667	42	0.430286	7	0.69134	2.899020***
	VAR48	EIC,FCPI,IRS,UR	0.096897	50	0.080314	45	0.986573	50	0.666667	42	0.391505	45	0.465462	2.567696**
	VAR49	EIC,CCI,IRS,UR	0.08874	25	0.075272	30	0.903526	25	0.684211	33	0.42844	12	2.017286**	3.206626***
	VEC12	EIC,CCLI,IRS,UR	0.083464	17	0.065732	14	0.849808	17	0.719298	15	0.409665	29	2.245949**	4.732179***
	VEC17	EIC,GDP,CCLI,IRS	0.08859	24	0.072805	22	0.901999	24	0.666667	42	0.430286	7	1.296026	2.871642***
	VEC26	EIC,GDP,CERI,IRS	0.077917	10	0.063457	8	0.793323	10	0.684211	33	0.392121	41	4.338017***	5.691975***
	VEC39	EIC,CERI,IRS,NEO	0.077206	7	0.059673	5	0.786089	7	0.719298	15	0.383195	46	2.700920***	5.067886***
	VEC46	EIC,CERI,IRS,UR	0.083522	18	0.065186	13	0.850395	18	0.719298	15	0.409665	29	2.026836**	4.291218***
	VEC50	EIC,CCLI,GDP,UR	0.095415	43	0.078065	35	0.971486	43	0.649123	46	0.410896	23	0.580655	1.752432*
Mixed	VEC06	EIC,GDP,CERI,NEO	0.077568	8	0.063603	9	0.78977	8	0.631579	49	0.320098	56	2.652171**	4.621209***
Models	VEC19	EIC,GDP,CCLI,CERI	0.081179	14	0.066602	15	0.826544	14	0.614035	53	0.330563	54	2.649097**	3.261268***
	VEC21	EIC,GDP,CERI,FCPI	0.077064	6	0.063929	11	0.784641	6	0.649123	46	0.32687	55	2.763788***	3.701637***
Twelve-months-ahead														
Benchmark	ARIMA	EIC	0.112777	48	0.093018	33	0.900335	48	0.607843	47	0.322184	49		
	FOCUS	ANY	0.079315	1	0.060467	1	0.633195	1	0.686275	3	0.351788	36	1.781936*	3.941355***
Top	VEC08	EIC,GDP,IRS,NEO	0.100702	8	0.080078	9	0.803933	8	0.666667	9	0.357555	24	0.695912	2.589813**
Winners	VEC22	EIC,CERI,FCPI,IRS	0.093074	2	0.071117	2	0.743038	2	0.705882	2	0.352172	35	0.699897	2.938006***
	VEC41	EIC,FCPI,IRS,NEO	0.100497	6	0.080472	10	0.8023	6	0.666667	9	0.357555	24	0.629907	3.124545***
	VAR20	EIC,CCLI,CERI,FCPI	0.104803	18	0.08777	20	0.836676	18	0.666667	9	0.37178	1	1.300921	8.404802***
	VAR29	EIC,CCLI,CCI,CERI	0.10416	15	0.089028	24	0.831543	15	0.627451	28	0.369473	19	1.168547	3.575228***
	VAR34	EIC,CCI,CERI,FCPI	0.10544	21	0.089299	25	0.841763	21	0.647059	19	0.354479	30	0.771536	2.997426***
	VAR37	EIC,CERI,FCPI,NEO	0.108615	29	0.092305	32	0.867104	29	0.647059	19	0.354479	30	0.386882	1.999173*
	VAR38	EIC,CCI,CERI,NEO	0.106387	24	0.090367	28	0.849317	24	0.647059	19	0.354479	30	0.014687	2.361638**
	VAR40	EIC,CCI,FCPI,NEO	0.106674	25	0.091399	29	0.851614	25	0.627451	28	0.352172	35	0.57651	2.328046**
	VEC14	EIC,GDP,CERI,UR	0.104271	16	0.080874	11	0.832425	16	0.666667	9	0.332564	46	0.339877	2.201437**
	VEC16	EIC,GDP,IRS,UR	0.110399	39	0.091572	30	0.881353	39	0.666667	9	0.357555	24	0.131544	1.222088
Strict	VEC18	EIC,GDP,CCLI,FCPI	0.111685	43	0.085951	14	0.891617	43	0.647059	19	0.33218	47	0.054477	1.576396
Winners	VEC23	EIC,CCLI,FCPI,IRS	0.106117	23	0.087005	17	0.847162	23	0.647059	19	0.354479	30	0.351823	2.112751**
	VEC24	EIC,GDP,FCPI,IRS	0.095521	3	0.075279	4	0.76257	3	0.627451	28	0.352172	35	1.038596	2.528937**
	VEC42	EIC,CCI,IRS,NEO	0.104942	19	0.086758	16	0.837787	19	0.627451	28	0.337947	42	0.520816	2.576181**
	VEC04	EIC,CCLI,IRS,NEO	0.098111	4	0.078335	5	0.783254	4	0.627451	28	0.352172	35	0.784725	3.125725***
	VEC06	EIC,GDP,CERI,NEO	0.101978	10	0.078854	8	0.814125	10	0.647059	19	0.325644	48	0.403997	2.361233**
	VEC12	EIC,CCLI,IRS,UR	0.105626	22	0.086135	15	0.843248	22	0.705882	2	0.366013	20	0.34873	1.558721
Weak	MEDIAN	ALL	0.105249	20	0.089577	26	0.840238	20	0.607843	47	0.369473	19	0.827318	2.890121***
Winners	VAR44	EIC,CERI,FCPI,UR	0.102617	13	0.088252	22	0.819225	13	0.607843	47	0.369473	19	0.961505	3.708550***
	VAR49	EIC,CCI,IRS,UR	0.104548	17	0.089927	27	0.834635	17	0.607843	47	0.369473	19	0.981337	3.732092***
	DMSE	ALL	0.102121	11	0.084403	12	0.815261	11	0.588235	55	0.349865	41	1.031005	3.180739***
	MEAN	ALL	0.102555	12	0.084968	13	0.818725	12	0.588235	55	0.349865	41	1.03006	3.178178***
	MRBEST	ANY	0.100624	7	0.078775	7	0.803311	7	0.607843	47	0.306036	55	0.401556	2.555561**
	VAR01	EIC,CCLI,FCPI,NEO	0.113476	51	0.096643	47	0.905912	51	0.607843	47	0.334871	43	-0.069804	1.58021
	VAR02	EIC,CCLI,CERI,NEO	0.11093	42	0.095262	41	0.885587	42	0.627451	28	0.352172	35	0.22307	2.169926**
	VAR03	EIC,CCLI,CCI,NEO	0.112357	46	0.097744	51	0.896982	46	0.607843	47	0.369473	19	0.051379	2.107828**
	VAR05	EIC,GDP,FCPI,NEO	0.109566	31	0.095177	40	0.874702	31	0.607843	47	0.369473	19	0.395162	2.687968***
	VAR07	EIC,GDP,CCI,NEO	0.110078	36	0.095424	42	0.878784	36	0.627451	28	0.369473	19	0.292812	2.412415**
Mixed	VAR09	EIC,CCLI,FCPI,UR	0.110299	38	0.096436	46	0.880553	38	0.647059	19	0.370242	2	0.291311	2.909310***
Models	VAR10	EIC,CCLI,CERI,UR	0.111855	45	0.097791	52	0.892976	45	0.607843	47	0.350634	38	0.106028	1.972915*
	VAR11	EIC,CCLI,CCI,UR	0.111738	44	0.096329	45	0.892037	44	0.607843	47	0.369473	19	0.103784	2.637242**
	VAR13	EIC,GDP,FCPI,UR	0.113455	50	0.098688	54	0.905747	50	0.647059	19	0.354479	30	-0.073214	2.014010**
	VAR15	EIC,GDP,CCI,UR	0.109965	34	0.094512	37	0.877885	34	0.607843	47	0.369473	19	0.263257	2.274353**
	VAR25	EIC,CCLI,CERI,IRS	0.112794	49	0.096653	48	0.900467	49	0.607843	47	0.369473	19	-0.00158	1.905496*
	VAR27	EIC,CCLI,CCI,IRS	0.11498	53	0.098011	53	0.917919	53	0.607843	47	0.369473	19	-0.245635	1.245483
	VAR30	EIC,CCLI,GDP,CCI	0.114784	52	0.099409	55	0.916357	52	0.607843	47	0.369473	19	-0.219313	1.797593*
	VAR31	EIC,CCI,FCPI,IRS	0.110025	35	0.095072	39	0.878366	35	0.607843	47	0.350634	38	0.248461	1.960048*
	VAR32	EIC,CCI,CERI,IRS	0.108652	30	0.091826	31	0.867398	30	0.588235	55	0.318339	51	0.312792	2.020961**

Table 15: Forecasting EI Claims in Quebec (cont)

(1)	Model (2)	Information Set (3)	RMSE (4)	Rank (5)	MAE (6)	Rank (7)	U-Theil (8)	Rank (9)	CI (10)	Rank (11)	DA (12)	Rank (13)	DM (14)	HLN (15)
Twelve-months-ahead														
	VAR33	EIC,GDP,CCI,IRS	0.110804	40	0.095991	43	0.884579	40	0.607843	47	0.369473	19	0.184998	1.919321*
	VAR35	EIC,GDP,CCI,FCPI	0.108427	28	0.093867	35	0.865603	28	0.627451	28	0.369473	19	0.458172	2.467405**
	VAR36	EIC,GDP,CCI,CERI	0.108297	27	0.093927	36	0.864571	27	0.588235	55	0.349865	41	0.673429	9.892223***
	VAR38	EIC,CCLI,CCI,FCPI	0.112641	47	0.096779	49	0.899244	47	0.588235	55	0.332564	46	0.587993	2.045106**
	VAR43	EIC,CCLI,GDP,NEO	0.121216	56	0.10405	56	0.967701	56	0.607843	47	0.369473	19	-0.529524	0.457913
	VAR45	EIC,CCI,CERI,UR	0.103384	14	0.08822	21	0.825342	14	0.588235	55	0.332564	46	0.855245	2.802672***
Mixed	VAR47	EIC,CCI,FCPI,UR	0.110159	37	0.096887	50	0.879435	37	0.627451	28	0.369473	19	0.22664	2.919071***
Models	VAR48	EIC,FCPI,IRS,UR	0.109926	33	0.094751	38	0.877573	33	0.647059	19	0.354479	30	0.312996	2.370386**
	VEC17	EIC,GDP,CCLI,IRS	0.119079	55	0.093398	34	0.950643	55	0.607843	47	0.369473	19	-0.233562	0.771468
	VEC19	EIC,GDP,CCLI,CERI	0.107735	26	0.088442	23	0.860085	26	0.568627	56	0.286428	56	0.20581	2.370881**
	VEC21	EIC,GDP,CERI,FCPI	0.098604	5	0.075278	3	0.787184	5	0.647059	19	0.321799	50	0.615923	2.848051***
	VEC26	EIC,GDP,CERI,IRS	0.109667	32	0.087404	18	0.875507	32	0.588235	55	0.30719	53	0.122298	1.464146
	VEC39	EIC,CERI,IRS,NEO	0.101302	9	0.078367	6	0.808724	9	0.607843	47	0.306036	55	0.351935	2.257996**
	VEC46	EIC,CERI,IRS,UR	0.110833	41	0.087424	19	0.884814	41	0.588235	55	0.30719	53	0.078458	1.575791
	VEC50	EIC,CCLI,GDP,UR	0.11762	54	0.096063	44	0.938995	54	0.666667	9	0.357555	24	-0.464494	1.067549

Table 16: Forecasting EI Claims in Ontario

(1)	Model (2)	Information Set (3)	RMSE (4)	Rank (5)	MAE (6)	Rank (7)	U-Theil (8)	Rank (9)	CI (10)	Rank (11)	DA (12)	Rank (13)	DM (14)	HLN (15)
One-month-ahead														
Benchmark	ARIMA	EIC	0.085581	53	0.064532	46	1.027356	53	0.596774	53	0.299168	52		
Top	DMSE	ALL	0.069178	3	0.053614	2	0.830447	3	0.709677	7	0.361082	10	1.796307*	2.588704**
Winners	MEAN	ALL	0.069126	2	0.053971	3	0.829825	2	0.725806	3	0.366805	6	1.809191*	2.558995**
	MEDIAN	ALL	0.06961	4	0.054444	7	0.83564	4	0.709677	7	0.361082	10	1.698027*	2.535188**
	MRBEST	ALL	0.078477	37	0.061988	40	0.94208	37	0.677419	17	0.340791	19	1.105498	2.264727**
	VAR03	EIC,CCLI,CCI,NEO	0.075397	22	0.057323	13	0.905106	22	0.709677	7	0.354839	12	1.036927	2.809565***
	VAR28	EIC,CCLI,CCI,FCPI	0.078574	38	0.059839	32	0.943243	38	0.709677	7	0.35692	11	0.735365	2.431530**
	VAR30	EIC,CCLI,GDP,CCI	0.070589	6	0.054377	6	0.847383	6	0.693548	11	0.347555	16	1.464647	2.676439***
	VAR32	EIC,CCI,CERI,IRS	0.074912	16	0.059776	31	0.899279	16	0.66129	26	0.334547	27	1.826494*	2.484993**
	VAR38	EIC,CCI,CERI,NEO	0.080051	43	0.060948	36	0.960974	43	0.645161	33	0.322581	38	1.53216	2.424168**
	VAR45	EIC,CCI,CERI,UR	0.074927	17	0.057877	17	0.899464	17	0.612903	48	0.312695	48	1.115234	2.797721***
	VAR47	EIC,CCI,FCPI,UR	0.075523	23	0.055727	10	0.906614	23	0.741935	1	0.377211	3	0.993206	2.630377**
	VAR49	EIC,CCI,IRS,UR	0.076328	26	0.059478	29	0.916285	26	0.645161	33	0.324662	32	1.000045	2.501161**
	VEC04	EIC,CCLI,IRS,NEO	0.078861	40	0.062667	42	0.946689	40	0.66129	26	0.334547	27	0.937402	2.281687**
	VEC07	EIC,GDP,CCI,NEO	0.073792	11	0.05939	27	0.885836	11	0.612903	48	0.318939	40	1.307017	2.582124**
	VEC10	EIC,CCLI,CERI,UR	0.075112	20	0.059216	26	0.901685	20	0.612903	48	0.312695	48	1.027335	2.199514**
	VEC11	EIC,CCLI,CCI,UR	0.079312	41	0.0615	39	0.952107	41	0.629032	42	0.380853	2	0.486996	2.427315**
	VEC14	EIC,GDP,CERI,UR	0.070946	8	0.055014	8	0.851674	8	0.629032	42	0.318418	44	1.535126	2.472092**
	VEC15	EIC,GDP,CCI,UR	0.077001	31	0.059207	25	0.924365	31	0.677419	17	0.382414	1	0.690268	2.564897**
	VEC17	EIC,GDP,CCLI,IRS	0.077432	34	0.06006	33	0.929539	34	0.693548	11	0.347555	16	0.923419	2.411049**
	VEC18	EIC,GDP,CCLI,FCPI	0.077024	32	0.057922	19	0.924638	32	0.612903	48	0.318939	40	0.817047	2.356903**
Strict	VEC19	EIC,GDP,CCLI,CERI	0.073659	10	0.055614	9	0.884239	10	0.629032	42	0.318418	44	1.247376	2.346232**
Winners	VEC20	EIC,CCLI,CERI,FCPI	0.074851	15	0.056536	12	0.898546	15	0.645161	33	0.322581	38	1.20876	2.375632**
	VEC21	EIC,GDP,CERI,FCPI	0.076523	29	0.058364	21	0.918623	29	0.629032	42	0.318418	44	0.963904	2.257386**
	VEC22	EIC,CERI,FCPI,IRS	0.077305	33	0.061088	37	0.928004	33	0.629032	42	0.323621	34	1.910868*	2.646542**
	VEC23	EIC,CCLI,FCPI,IRS	0.076921	30	0.059625	30	0.923401	30	0.677419	17	0.340791	19	0.853354	2.375920**
	VEC24	EIC,GDP,FCPI,IRS	0.074583	13	0.057982	20	0.895338	13	0.693548	11	0.350676	14	1.142342	2.403750**
	VEC25	EIC,CCLI,CERI,IRS	0.072848	9	0.056068	11	0.87451	9	0.677419	17	0.33871	23	1.300531	2.384912**
	VEC26	EIC,GDP,CERI,IRS	0.070718	7	0.054162	4	0.848931	7	0.629032	42	0.318418	44	1.621997	2.352379**
	VEC27	EIC,CCLI,CCI,IRS	0.076209	25	0.059049	23	0.914855	25	0.66129	26	0.334547	27	0.796955	2.552546**
	VEC29	EIC,CCLI,CCI,CERI	0.068151	1	0.053303	1	0.818115	1	0.66129	26	0.33975	20	1.756031*	2.686913***
	VEC31	EIC,CCI,FCPI,IRS	0.080971	44	0.063151	44	0.972015	44	0.693548	11	0.363163	8	0.712745	2.493037**
	VEC33	EIC,GDP,CCI,IRS	0.076354	27	0.059097	24	0.916597	27	0.66129	26	0.334547	27	0.784352	2.505382**
	VEC34	EIC,CCI,CERI,FCPI	0.075006	19	0.057641	15	0.900408	19	0.725806	3	0.372008	4	2.109600**	2.821992***
	VEC35	EIC,GDP,CCI,FCPI	0.074961	18	0.060366	35	0.899867	18	0.66129	26	0.347034	17	1.541537	2.701033***
	VEC36	EIC,GDP,CCI,CERI	0.069627	5	0.054314	5	0.835843	5	0.629032	42	0.323621	34	1.672899*	2.611753**
	VEC37	EIC,CERI,FCPI,NEO	0.074352	12	0.057899	18	0.892555	12	0.677419	17	0.33871	23	1.547732	2.644358**
	VEC40	EIC,CCI,FCPI,NEO	0.078838	39	0.062457	41	0.946411	39	0.66129	26	0.367846	5	0.741011	2.572788**
	VEC41	EIC,FCPI,IRS,NEO	0.083377	50	0.06435	45	1.000902	50	0.677419	17	0.33871	23	0.269044	2.645000**
	VEC42	EIC,CCI,IRS,NEO	0.077642	35	0.062923	43	0.932055	35	0.645161	33	0.322581	38	0.835744	2.358835**
	VEC43	EIC,CCLI,GDP,NEO	0.074698	14	0.057675	16	0.896711	14	0.612903	48	0.308533	49	1.097772	2.690879***
	VEC44	EIC,CERI,FCPI,UR	0.078321	36	0.061119	38	0.940209	36	0.66129	26	0.331426	29	0.733742	2.446683**
	VEC48	EIC,FCPI,IRS,UR	0.084416	51	0.065277	51	1.013378	51	0.66129	26	0.331426	29	0.147239	2.022547**
	VEC50	EIC,CCLI,GDP,UR	0.075667	24	0.058627	22	0.908346	24	0.645161	33	0.322581	38	0.951539	2.745592***

Table 16: Forecasting EI Claims in Ontario (cont)

(1)	Model (2)	Information Set (3)	RMSE (4)	Rank (5)	MAE (6)	Rank (7)	U-Theil (8)	Rank (9)	CI (10)	Rank (11)	DA (12)	Rank (13)	DM (14)	HLN (15)
One-month-ahead														
	VAR05	EIC,GDP,FCPI,NEO	0.07957	42	0.060117	34	0.955202	42	0.629032	42	0.315297	45	0.711169	2.670245***
Weakly Winners	VEC08	EIC,GDP,IRS,NEO	0.082651	48	0.064715	48	0.992187	48	0.596774	53	0.302289	50	0.321938	2.166939**
	FOCUS	ANY	0.081234	45	0.064597	47	0.97518	45	0.548387	56	0.274194	56	0.576537	2.213785**
	VAR01	EIC,CCLI,FCPI,NEO	0.08541	52	0.065962	52	1.025303	52	0.645161	33	0.324662	32	0.017825	2.299411**
	VEC02	EIC,CCLI,CERI,NEO	0.075217	21	0.059426	28	0.902938	21	0.596774	53	0.299168	52	1.237551	2.350515**
	VEC06	EIC,GDP,CERI,NEO	0.076419	28	0.057501	14	0.917378	28	0.596774	53	0.298127	53	1.411789	2.359260**
Mixed Models	VEC09	EIC,CCLI,FCPI,UR	0.082249	47	0.065201	50	0.987358	47	0.612903	48	0.364724	7	0.299674	2.330233**
	VEC13	EIC,GDP,FCPI,UR	0.081681	46	0.066029	53	0.98054	46	0.629032	42	0.330905	30	0.391523	2.607510**
	VEC16	EIC,GDP,IRS,UR	0.085604	55	0.067338	55	1.027635	55	0.596774	53	0.314776	46	-0.002817	1.740869*
	VEC39	EIC,CERI,IRS,NEO	0.088549	56	0.066064	54	1.062993	56	0.645161	33	0.353798	13	-0.365088	2.496302**
	VEC46	EIC,CERI,IRS,UR	0.082672	49	0.064736	49	0.992438	49	0.548387	56	0.286681	55	0.353834	2.100933**
Strictly Losers	VEC12	EIC,CCLI,IRS,UR	0.085586	54	0.068063	56	1.027418	54	0.580645	54	0.292404	54	-0.000605	1.706997*
Six-months-ahead														
Benchmark	ARIMA	EIC	0.180945	52	0.133332	52	1.114415	52	0.45614	56	0.240074	56		
Top Winners	VEC23	EIC,CCLI,FCPI,IRS	0.099331	2	0.078245	1	0.611767	2	0.77193	3	0.391505	9	1.721530*	2.121940**
	VEC37	EIC,CERI,FCPI,NEO	0.101072	4	0.08681	4	0.622486	4	0.789474	1	0.394891	7	1.568467	2.093278**
	DMSE	ALL	0.107239	5	0.08969	8	0.660472	5	0.77193	3	0.397969	6	1.704040*	1.996227*
	MEAN	ALL	0.110288	8	0.09212	10	0.679251	8	0.736842	12	0.389351	11	1.702327*	1.985960*
	MEDIAN	ALL	0.115883	11	0.095509	12	0.713705	11	0.754386	6	0.393352	8	1.676841*	1.942785*
	MRBEST	ANY	0.108526	7	0.088357	6	0.668399	7	0.701754	20	0.371807	18	1.525111	2.090699**
	VAR03	EIC,CCLI,CCI,NEO	0.159575	45	0.119527	41	0.982799	45	0.666667	31	0.338873	34	0.51048	1.955160*
	VAR28	EIC,CCLI,CCI,FCPI	0.13849	29	0.108295	28	0.852942	29	0.701754	20	0.362881	24	1.302547	2.082582**
	VAR30	EIC,CCLI,GDP,CCI	0.125644	16	0.102457	18	0.773822	16	0.754386	6	0.385657	13	1.283233	1.955684*
	VAR32	EIC,CCI,CERI,IRS	0.145468	37	0.115954	36	0.895916	37	0.631579	38	0.348107	31	0.872994	1.67017
	VAR38	EIC,CCI,CERI,NEO	0.1622	47	0.123613	45	0.998969	47	0.631579	38	0.361958	25	0.43646	1.912131*
	VAR45	EIC,CCI,CERI,UR	0.147791	39	0.117993	39	0.910223	39	0.684211	28	0.368421	23	0.819977	1.797742*
	VAR47	EIC,CCI,FCPI,UR	0.143761	36	0.1163	37	0.885401	36	0.701754	20	0.356417	27	1.033863	1.823313*
	VAR49	EIC,CCI,IRS,UR	0.124652	15	0.103328	19	0.767716	15	0.631579	38	0.327793	38	1.270217	1.924370*
	VEC04	EIC,CCLI,IRS,NEO	0.155226	42	0.113314	30	0.956017	42	0.649123	32	0.32687	40	1.442226	2.400899**
	VEC07	EIC,GDP,CCI,NEO	0.127045	19	0.098895	15	0.782451	19	0.736842	12	0.389351	11	1.628942	1.981813*
	VEC10	EIC,CCLI,CERI,UR	0.142304	34	0.117063	38	0.876429	34	0.561404	51	0.286242	51	1.124024	1.626939
	VEC11	EIC,CCLI,CCI,UR	0.123725	14	0.099003	16	0.762004	14	0.666667	31	0.414589	2	1.479159	2.046888**
	VEC14	EIC,GDP,CERI,UR	0.137287	28	0.114132	33	0.845529	28	0.596491	48	0.330563	36	1.23586	1.659662
	VEC15	EIC,GDP,CCI,UR	0.121304	12	0.095855	13	0.747097	12	0.736842	12	0.430902	1	1.320139	2.101784**
	VEC17	EIC,GDP,CCLI,IRS	0.140952	31	0.108027	27	0.868105	31	0.631579	38	0.317328	43	1.367677	2.052262**
	VEC18	EIC,GDP,CCLI,FCPI	0.136923	27	0.114103	32	0.843287	27	0.684211	28	0.38104	14	1.224284	1.698074*
	VEC19	EIC,GDP,CCLI,CERI	0.142332	35	0.114272	35	0.876603	35	0.666667	31	0.345337	32	1.126975	1.714174*
	VEC20	EIC,CCLI,CERI,FCPI	0.140972	32	0.120054	42	0.868228	32	0.596491	48	0.299169	49	1.193623	1.800192*
Strict Winners	VEC21	EIC,GDP,CERI,FCPI	0.129681	21	0.106409	23	0.798688	21	0.631579	38	0.316713	44	1.312974	1.813508*
	VEC22	EIC,CERI,FCPI,IRS	0.12623	18	0.093683	11	0.777431	18	0.719298	14	0.373653	17	1.474825	2.121070**
	VEC24	EIC,GDP,FCPI,IRS	0.113943	10	0.091035	9	0.70176	10	0.684211	28	0.350569	30	1.59701	2.004225**
	VEC25	EIC,CCLI,CERI,IRS	0.131511	23	0.106557	24	0.809959	23	0.614035	44	0.307479	47	1.381704	1.814813*
	VEC26	EIC,GDP,CERI,IRS	0.129393	20	0.105764	22	0.796912	20	0.614035	44	0.333333	35	1.524868	1.697905*
	VEC27	EIC,CCLI,CCI,IRS	0.098697	1	0.080203	2	0.607861	1	0.684211	28	0.368421	23	1.572112	2.131374**
	VEC29	EIC,CCLI,CCI,CERI	0.121439	13	0.09718	14	0.747925	13	0.684211	28	0.368421	23	1.633061	1.832143*
	VEC31	EIC,CCI,FCPI,IRS	0.130234	22	0.100484	17	0.802096	22	0.719298	14	0.385965	12	1.301915	2.016991**
	VEC33	EIC,GDP,CCI,IRS	0.099727	3	0.081932	3	0.614204	3	0.684211	28	0.358264	26	1.504595	2.111858**
	VEC34	EIC,CCI,CERI,FCPI	0.162715	48	0.123628	46	1.002139	48	0.736842	12	0.369344	19	0.566732	1.744086*
	VEC35	EIC,GDP,CCI,FCPI	0.132533	24	0.106867	25	0.816254	24	0.701754	20	0.413358	3	1.229595	1.832170*
	VEC36	EIC,GDP,CCI,CERI	0.107938	6	0.089323	7	0.664776	6	0.736842	12	0.400739	4	1.634248	1.892522*
	VEC40	EIC,CCI,FCPI,NEO	0.145566	38	0.114006	31	0.896523	38	0.614035	44	0.398584	5	0.770233	1.663956
	VEC41	EIC,FCPI,IRS,NEO	0.178718	51	0.123515	44	1.100697	51	0.736842	12	0.373961	16	0.048476	1.970622*
	VEC42	EIC,CCI,IRS,NEO	0.160395	46	0.126185	49	0.987851	46	0.596491	48	0.327485	39	0.91249	1.860507*
	VEC43	EIC,CCLI,GDP,NEO	0.155189	41	0.124194	47	0.955785	41	0.614035	44	0.315482	45	1.147245	2.622045**
	VEC44	EIC,CERI,FCPI,UR	0.125791	17	0.105669	21	0.77473	17	0.684211	28	0.344414	33	1.319947	1.994166*
	VEC48	EIC,FCPI,IRS,UR	0.140313	30	0.105358	20	0.864166	30	0.701754	20	0.350877	29	1.59414	1.799560*
	VEC50	EIC,CCLI,GDP,UR	0.141601	33	0.114262	34	0.872103	33	0.561404	51	0.282241	53	1.407765	2.185611**
	FOCUS	ANY	0.110765	9	0.087371	5	0.682184	9	0.754386	6	0.377347	15	1.576388	2.027288**
	VEC02	EIC,CCLI,CERI,NEO	0.134127	26	0.107566	26	0.826067	26	0.631579	38	0.327793	38	1.514059	1.990587*
	VEC06	EIC,GDP,CERI,NEO	0.152078	40	0.119036	40	0.936629	40	0.701754	20	0.352416	28	1.105535	1.652804
	VEC09	EIC,CCLI,FCPI,UR	0.132833	25	0.112412	29	0.818097	25	0.684211	28	0.368421	23	1.136026	1.961374*
	VEC12	EIC,CCLI,IRS,UR	0.162809	49	0.128206	50	1.002719	49	0.596491	48	0.299785	48	0.631497	1.581718
	VEC13	EIC,GDP,FCPI,UR	0.163625	50	0.131417	51	1.007746	50	0.614035	44	0.323176	41	0.463661	1.771719*
	VEC16	EIC,GDP,IRS,UR	0.159144	44	0.121104	43	0.980145	44	0.614035	44	0.310249	46	0.804485	1.696690*
	VEC46	EIC,CERI,IRS,UR	0.156014	43	0.125635	48	0.960866	43	0.526316	54	0.292398	50	0.835364	1.522033
	VAR01	EIC,CCLI,FCPI,NEO	0.19399	54	0.145957	53	1.19476	54	0.508772	55	0.25454	55	-0.405183	1.54675
	VAR05	EIC,GDP,FCPI,NEO	0.190488	53	0.148525	55	1.173192	53	0.561404	51	0.282241	53	-0.283958	1.622589

Table 16: Forecasting EI Claims in Ontario (cont)

(1)	Model (2)	Information Set (3)	RMSE (4)	Rank (5)	MAE (6)	Rank (7)	U-Theil (8)	Rank (9)	CI (10)	Rank (11)	DA (12)	Rank (13)	DM (14)	HLN (15)
Six-months-ahead														
Mixed Models	VEC08	EIC,GDP,IRS,NEO	0.199702	56	0.146409	54	1.229939	56	0.54386	53	0.272084	54	-0.860367	1.839440*
	VEC39	EIC,CERI,IRS,NEO	0.196701	55	0.155608	56	1.211453	55	0.54386	53	0.321945	42	-1.085532	1.632962
Twelve-months-ahead														
Benchmark	ARIMA	EIC	0.268806	56	0.20153	55	1.115201	56	0.509804	56	0.259131	56		
Top Winners	VEC23	EIC,CCLI,FCPI,IRS	0.139398	1	0.10724	1	0.578325	1	0.803922	4	0.401	6	1.088004	1.773247*
	VEC48	EIC,FCPI,IRS,UR	0.153526	3	0.113839	2	0.636936	3	0.823529	2	0.417532	1	0.96987	1.640931
	DMSE	ALL	0.166998	8	0.13066	8	0.692826	8	0.745098	14	0.372549	17	0.968361	1.652093
	MEAN	ALL	0.170976	10	0.134079	12	0.709332	10	0.72549	15	0.370242	19	0.946745	1.61261
	MEDIAN	ALL	0.171829	11	0.132852	10	0.712868	11	0.745098	14	0.376778	14	0.900457	1.51844
	MRBEST	ANY	0.174806	14	0.134897	13	0.725223	14	0.784314	6	0.391003	9	0.818325	2.011310**
	VAR03	EIC,CCLI,CCI,NEO	0.226225	43	0.181474	45	0.938546	43	0.568627	51	0.312572	48	0.552575	1.792635*
	VAR28	EIC,CCLI,CCI,FCPI	0.223651	42	0.183979	50	0.927866	42	0.686275	26	0.350634	31	1.118025	2.319979**
	VAR30	EIC,CCLI,GDP,CCI	0.21162	34	0.176703	42	0.877954	34	0.647059	39	0.351788	29	0.844791	1.780527*
	VAR32	EIC,CCI,CERI,IRS	0.227923	44	0.188012	52	0.945588	44	0.54902	53	0.278739	53	0.758869	1.592379
	VAR38	EIC,CCI,CERI,NEO	0.204485	30	0.168142	38	0.84835	30	0.568627	51	0.312572	48	0.687959	1.724135*
	VAR45	EIC,CCI,CERI,UR	0.220165	40	0.180704	44	0.913404	40	0.588235	46	0.329489	41	0.746375	1.811763*
	VAR47	EIC,CCI,FCPI,UR	0.217047	39	0.181546	46	0.900467	39	0.627451	41	0.317955	46	0.729698	1.646154
	VAR49	EIC,CCI,IRS,UR	0.222973	41	0.179465	43	0.925051	41	0.529412	55	0.263745	55	0.574544	1.849268*
	VEC04	EIC,CCLI,IRS,NEO	0.215988	38	0.161301	34	0.896072	38	0.745098	14	0.378316	13	0.844497	1.674004
	VEC07	EIC,GDP,CCI,NEO	0.207957	33	0.161149	33	0.862755	33	0.568627	51	0.286044	52	0.603881	1.303087
	VEC10	EIC,CCLI,CERI,UR	0.1882	24	0.142121	17	0.780788	24	0.686275	26	0.342176	38	0.722807	1.351824
	VEC11	EIC,CCLI,CCI,UR	0.266371	55	0.186036	51	1.105099	55	0.627451	41	0.365629	23	0.020051	2.261513**
	VEC14	EIC,GDP,CERI,UR	0.179757	19	0.146761	23	0.74576	19	0.666667	32	0.355248	26	0.81796	1.438692
	VEC15	EIC,GDP,CCI,UR	0.249607	51	0.167448	37	1.03555	51	0.666667	32	0.368704	20	0.156553	2.091290**
	VEC17	EIC,GDP,CCLI,IRS	0.173483	13	0.135464	14	0.719732	13	0.764706	8	0.381776	12	1.015748	1.722692*
	VEC18	EIC,GDP,CCLI,FCPI	0.17603	16	0.14522	22	0.730298	16	0.705882	18	0.35717	24	0.818326	1.432363
	VEC19	EIC,GDP,CCLI,CERI	0.177649	18	0.14231	18	0.737015	18	0.666667	32	0.337562	40	0.821267	1.455701
	VEC20	EIC,CCLI,CERI,FCPI	0.188745	25	0.147499	24	0.78305	25	0.686275	26	0.352557	27	0.728174	1.402543
	VEC21	EIC,GDP,CERI,FCPI	0.175034	15	0.142851	19	0.726168	15	0.686275	26	0.344867	35	0.835654	1.441484
	VEC22	EIC,CERI,FCPI,IRS	0.154475	4	0.12134	5	0.640874	4	0.705882	18	0.409458	3	0.948518	1.791222*
	VEC24	EIC,GDP,FCPI,IRS	0.162601	5	0.120815	4	0.674584	5	0.745098	14	0.371396	18	0.916645	1.56505
Strict Winners	VEC25	EIC,CCLI,CERI,IRS	0.19503	28	0.143702	20	0.809123	28	0.647059	39	0.355248	26	0.648202	1.365715
	VEC26	EIC,GDP,CERI,IRS	0.172539	12	0.133335	11	0.715818	12	0.666667	32	0.344867	35	0.84826	1.443129
	VEC27	EIC,CCLI,CCI,IRS	0.262936	54	0.183741	49	1.090847	54	0.647059	39	0.366782	22	0.058225	2.575085**
	VEC29	EIC,CCLI,CCI,CERI	0.212359	35	0.15804	29	0.881019	35	0.647059	39	0.32526	43	0.561349	1.367996
	VEC31	EIC,CCI,FCPI,IRS	0.177174	17	0.13235	9	0.735043	17	0.686275	26	0.342176	38	0.811841	1.452415
	VEC33	EIC,GDP,CCI,IRS	0.247082	50	0.174086	41	1.025075	50	0.745098	14	0.394464	7	0.260684	2.475101**
	VEC34	EIC,CCI,CERI,FCPI	0.189339	26	0.150818	28	0.785516	26	0.647059	39	0.342561	36	0.715719	1.369458
	VEC35	EIC,GDP,CCI,FCPI	0.207626	32	0.150599	27	0.861381	32	0.686275	26	0.38639	10	0.546145	1.615458
	VEC36	EIC,GDP,CCI,CERI	0.213993	36	0.160842	32	0.887796	36	0.568627	51	0.300654	51	0.563728	1.441087
	VEC37	EIC,CERI,FCPI,NEO	0.148114	2	0.119046	3	0.614485	2	0.705882	18	0.351788	29	1.0584	1.809888*
	VEC40	EIC,CCI,FCPI,NEO	0.205543	31	0.165079	36	0.85274	31	0.647059	39	0.366782	22	0.99543	2.017388**
	VEC41	EIC,FCPI,IRS,NEO	0.16445	6	0.129755	7	0.682258	6	0.823529	2	0.412534	2	0.953696	1.627909
	VEC42	EIC,CCI,IRS,NEO	0.25523	52	0.182213	48	1.058876	52	0.529412	55	0.405998	4	0.167072	1.07269
	VEC43	EIC,CCLI,GDP,NEO	0.236421	47	0.189779	53	0.980845	47	0.607843	45	0.320261	45	0.71591	1.991739*
	VEC44	EIC,CERI,FCPI,UR	0.164973	7	0.13593	15	0.684425	7	0.647059	39	0.32526	43	0.877207	1.605582
	VEC50	EIC,CCLI,GDP,UR	0.18538	22	0.144053	21	0.769091	22	0.686275	26	0.350634	31	0.975336	1.648091
	FOCUS	ANY	0.170066	9	0.122145	6	0.705557	9	0.745098	14	0.373318	15	0.898561	1.876279*
	VAR05	EIC,GDP,FCPI,NEO	0.246248	49	0.19352	54	1.021616	49	0.607843	45	0.305652	50	0.415459	1.506521
	VEC02	EIC,CCLI,CERI,NEO	0.233041	46	0.182077	47	0.966821	46	0.607843	45	0.320261	45	0.753652	1.516453
	VEC06	EIC,GDP,CERI,NEO	0.199551	29	0.158767	30	0.827881	29	0.686275	26	0.344867	35	0.747741	1.383303
	VEC08	EIC,GDP,IRS,NEO	0.229165	45	0.163479	35	0.950741	45	0.666667	32	0.3391	39	0.569593	1.224366
	VEC09	EIC,CCLI,FCPI,UR	0.190078	27	0.158945	31	0.788579	27	0.666667	32	0.344867	35	0.719294	1.377269
	VEC12	EIC,CCLI,IRS,UR	0.183902	20	0.147966	25	0.762959	20	0.784314	6	0.391003	9	0.867971	1.525584
	VEC13	EIC,GDP,FCPI,UR	0.214329	37	0.171451	40	0.889192	37	0.607843	45	0.311419	49	0.572145	1.262044
	VEC16	EIC,GDP,IRS,UR	0.184405	21	0.148015	26	0.765043	21	0.803922	4	0.401384	5	0.874269	1.531724
	VEC39	EIC,CERI,IRS,NEO	0.237918	48	0.168151	39	0.987055	48	0.568627	51	0.372549	17	0.380102	1.250466
	VEC46	EIC,CERI,IRS,UR	0.187897	23	0.141654	16	0.779532	23	0.764706	8	0.385236	11	0.739475	1.342817
Mixed Models	VAR01	EIC,CCLI,FCPI,NEO	0.260135	53	0.202012	56	1.079226	53	0.54902	53	0.27451	54	0.246638	1.975196*

Notes:

ALL refers to the information set of a combination procedure that involves all individual forecasts.

ANY refers to the information set of a combination procedure that places the full weight on a single forecast.