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Nowcasting the Unemployment Rate in Canada Using Google Trends Data

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ABSTRACT

Can Google trends data help forecast the unemployment rate in Canada? Extracting data from the Google Trends database on searches related to Employment Insurance (EI), we construct a Google index of the relative search intensity of terms related to EI. We find that the Google index is correlated to the unemployment rate and the number of EI beneficiaries. The Google index is therefore considered a leading variable, in that it could help forecast the unemployment rate and EI beneficiaries. We create a first-order autoregressive (AR(1)) model for the short-term forecast (nowcast) of the unemployment rate and the number of EI beneficiaries. We find that the Google index is statistically significant in forecasting the unemployment rate but not the number of EI beneficiaries. However, results of the sensitivity analysis suggest that the Google index is not helpful in forecasting the unemployment rate. With that said, the Google index may be more useful when there is a sudden change in the unemployment rate from one month to the next, and using this data to predict turning points is a potentially fruitful area for future research.

I INTRODUCTION

The timeliness of labour market data in Canada varies significantly. Some, like the unemployment rate, are released very soon after the end of the reference month. Others, like Employment Insurance (EI) claims, are released nearly two months following the end of the reference month. Regardless of the size of the lag, be it two weeks or two months, this creates the opportunity for value to be added through the development of models that forecast, over very short time horizons, the eventual outturn data before it is released. This is particularly true in the case of the unemployment rate, as financial markets and economic commentators look to this as one of the early indicators of the state of the economy.

In order to undertake these short-term forecasts, often referred to as nowcasts, we turn to Big Data. Big Data is a relatively new tool which researchers are increasingly turning to for finding answers to their questions. The Research Institute of the Finnish Economy (Tuhkuri, 2016a; Tuhkuri, 2016b) uses Google search data to produce forecasts of the unemployment rate in the United States and many European countries.

While Tuhkuri (2016a; 2016b) finds that Google searches do help predict the unemployment rate, this has never been done for Canada. As such, we use this methodology to publish nowcasts of the unemployment rate in Canada before the official numbers are released by Statistics Canada. This paper describes the methods used and analyzes the impact of Google search data in nowcasting the unemployment rate in Canada

II DATA

The data used for this paper are the Google Trends database as well as the unemployment rate from Statistics Canada and the number of EI (employment insurance) beneficiaries. Although the main goal of this paper is to nowcast the unemployment rate, we also apply our model to the EI beneficiaries as we hypothesize that perhaps Google searches for employment insurance benefits will better anticipate employment insurance claims than the unemployment rate.

a. Unemployment Rate

Unemployment rate data are from the Statistics Canada (2017b) Labour Force Survey. These results are published with a two week lag, hence the need for an accurate nowcast of these numbers. The unemployment rate is the number of unemployed persons expressed as a percentage of the labour force (Statistics Canada, 2017b). We use seasonally-adjusted data as these are the official numbers published by Statistics Canada that we hope to nowcast. These are also the labour market data that tend to be the focus of financial markets and economic commentators. Chart 1 shows the unemployment rate in Canada from December 2003 until January 2017.

Chart 1: Unemployment Rate in Canada 2004-2017

Sources: Statistics Canada, Institute of Fiscal Studies and Democracy.
Note: Seasonally adjusted.

b. EI beneficiaries

Data on the number of EI beneficiaries are from the Statistics Canada (2017a) Employment Insurance Statistics survey. These results are published with a two month lag, hence the need for an accurate nowcast of these numbers. The number of EI beneficiaries is a count of persons who qualified for employment insurance benefits during the Labour Force Survey reference week (Statistics Canada, 2017a). We use seasonally-adjusted data as these are the official numbers published by Statistics Canada that we hope to nowcast. Chart 2 shows the number of EI beneficiaries in Canada from December 2003 until December 2016.

Chart 2: EI Beneficiaries in Canada 2004-2017

Sources: Statistics Canada, Institute of Fiscal Studies and Democracy.
Note: Seasonally adjusted.

c. Google Trends Databse

The Google Trends database contains data on the volumes of Google searches. Users can identify specific search words and obtain information on the volume of searches for those specific terms. Google trends data are available from 2004 up to 36 hours prior to the downloading of the data. Google trends data do not provide information on the absolute volume of a search, but only of its evolution on a scale from 0 to 100. Search results are adjusted by dividing by the total searches of the geography and time range specified to compare relative popularity. The results are then scaled from 0 to 100 based on a topic's proportion to all searches on all topics. An index of 100 is given to the highest peak of a search. This allows to easily compare the relative search intensity of various terms.

Following the work of Tuhkuri (2016a; 2016b), we calculate the Google index. First, we identifie 37 keywords that are likely to be the first searches that a recently unemployed worker in Canada would type into Google. Then we identify those with the highest search volumes. The eight words with the highest search volume are: EI, employment insurance, *assurance emploi*, EI reporting, unemployment insurance, EI online, EI benefits, and EI login. As set out by Tuhkuri (2016b), we combine these by a Boolean search operator 'OR', to obtain the Google index from the Google Trends database. The Boolean search operator 'OR' means we are pulling searches which include any of the terms specified. Since the maximum number of terms that can be exported at one time is seven if the term "unemployment" is not included, but six if it is, we drop the term "unemployment insurance" in our final Google index. In a sensitivity analysis, we explore the impact on the results of excluding this term. Our final Google index is: EI OR employment insurance OR *assurance emploi* OR EI reporting OR EI online OR EI benefits OR EI login.[1]

Upon extracting the Google index from the Google trends database, we adjust for seasonality using additive decomposition. We choose to seasonally-adjust the Google index prior to running our model, rather than using unadjusted variables and seasonally adjusting the output of the model, because Statistics Canada uses its own method to seasonally-adjust data. Using unemployment rate data that were adjusted by Statistics Canada and adjusting the Google index prior to running the model should keep our results as comparable as possible with those of Statistics Canada. Chart 3 shows the Google index in Canada from January 2004 to February 2017. Comparing Chart 3 to Chart 1 and Chart 2, we see that the Google Trends data does not show similar peaks and troughs to the unemployment rate and EI claims.

The correlation between the Google index and the unemployment rate is 0.30 while the correlation between the Google index and EI beneficiaries is 0.36. Table 1 provides descriptive statistics for the unemployment rate, EI beneficiaries, and the Google index.

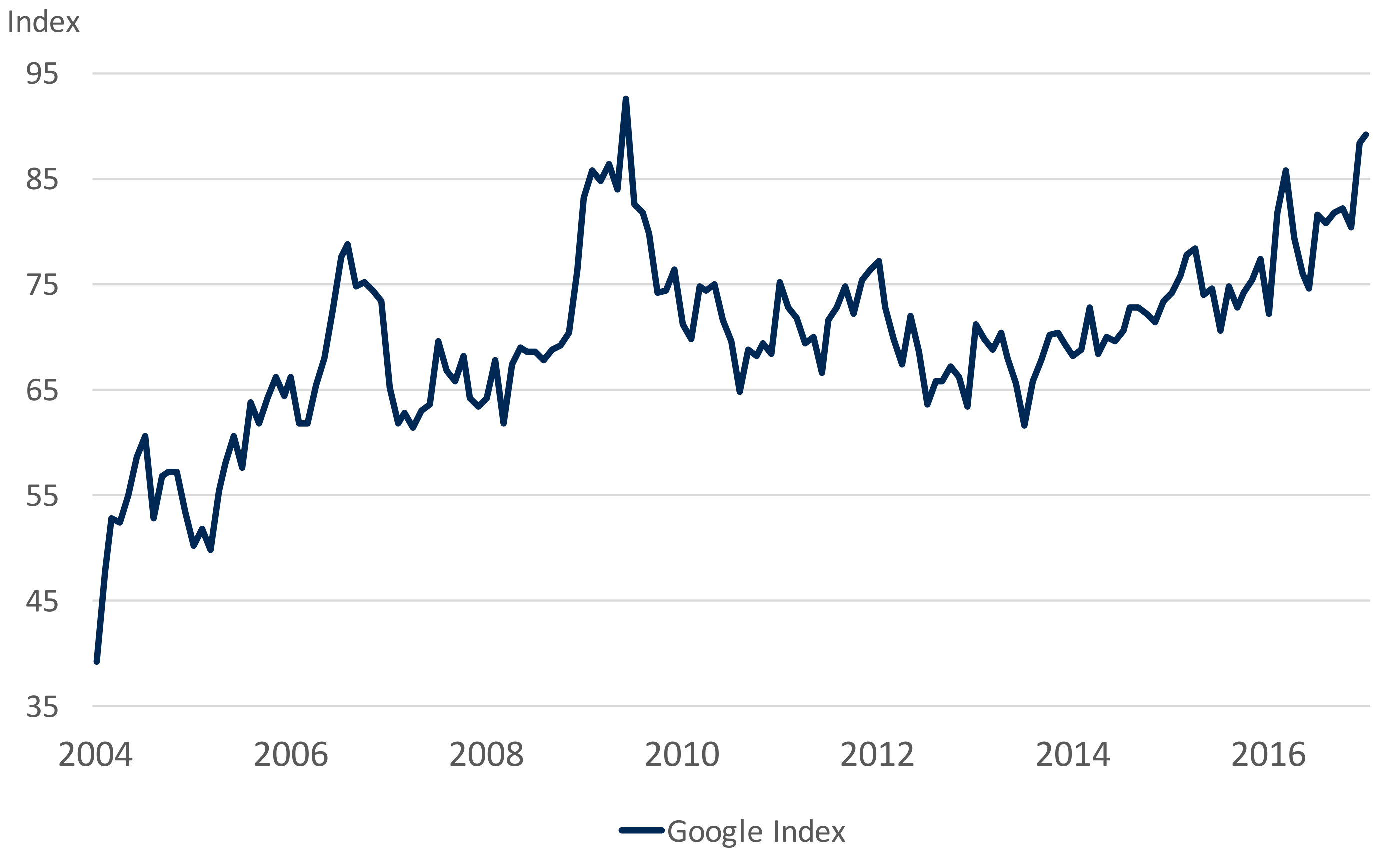
Table 1: Descriptive Statistics for the Unemployment Rate, the Number of EI Beneficiaries, and the Google Index 2004-2017

Variable	n	µ	σ	sk	k	min	max
Unemployment Rate	158	7.04	0.67	0.36	-0.11	5.8	8.7
EI Beneficiaries	157	570933.2	82323.38	1.61	1.56	488830	821960
Google Index	158	69.69	8.61	-0.32	0.77	39.09	92.49

Sources: Statistics Canada, Google Trends, Institute of Fiscal Studies and Democracy.
Note: Sample period December 2003-December 2016 for EI beneficiaries, December 2003 – January 2017 for the unemployment rate, and January 2004 – February 2017 for the Google index, n= sample size, µ=mean, σ= standard deviation, σ2=variance, sk=skewness, k=kurtosis, min=smallest value, and max=largest value.

1 The data for the Google index were extracted from the Google trends database on February 20th, 2017, for the period from January 1, 2004 to present.

Chart 3: Google Index in Canada 2004-2017



Sources: Google Trends Database, Institute of Fiscal Studies and Democracy.
Note: Seasonally adjusted.

III METHODS

This section describes the methods used to determine if the Google index helps to predict the unemployment rate and EI claims. For simplicity, in this section, we will call these the dependent variable. First we describe how we determine if the Google index and the dependent variable are correlated, and the causality. Then, we describe the model and methods to determine whether the Google index improves the model fit.

a Correlation and Causality

We determine the correlation between the Google index and the dependent variable using the cross-correlation function. The cross-correlation function describes the correlation between the dependent variable and the Google index at various lags of the Google index. This helps in determining the lead-lag relationship between the two variables. We then use a Granger Causality test to determine the direction of the causality between the two variables.

b The Model and Model Fit

This paper uses the same method as Tuhkuri (2016b) to nowcast the dependent variable. While

Tukhuri (2016b) uses a seasonal first-order autoregressive (AR(1)) model as the main benchmark, the model used here is adapted for the fact that we are using data which have already been seasonally adjusted. Because changes in the number of EI beneficiaries and the unemployment rate are more easily discussed as a percentage, we use a log transformation on the dependent variable. As described by Tuhkuri (2017b), the benchmark model (Model 0) is as follows:

$$\text{Model 0: } log\ (\ y_t) = \beta_0 + \beta_1\ log(\ y_{t-1}) + e_t$$

To predict the present, we extend the benchmark model with the Google index (Model 1). The extended model is as follows:

$$\text{Model 0: } log\ (\ y_t) = \beta_0 + \beta_1\ log(\ y_{t-1}) + \beta_e x_t + e_t$$

The dependent variable in month $_t$ is denoted by y_t while y_{t-1} denotes the dependent variable in the previous month. The Google index in month $_t$ is denoted by x_t while e_t represents the error term. We estimate the models over the entire observation period, and use Akaike (AIC) and Bayesian information criteria (BIC), statistical significance, and magnitude of parameters to compare model fit between the benchmark and extended models. We also compare the mean absolute percentage error of the models. Finally, we generate one-step-ahead rolling nowcasts of the benchmark and extended models from 2013 to 2017 and plot the results. For the unemployment rate, we also generate the evolution of the root-mean-square error (RMSE) of the extended model over the period from 2010 to 2017 as new data is added. Finally, as a sensitivity analysis, we compare various models used to predict the unemployment rate to explore the impact of varying the Google Trends search terms, of varying the number of decimals included in the unemployment rate, of using seasonally-adjusted or unadjusted unemployment data, and of varying the date at which the Google Trends data were downloaded.

IV RESULTS

This section first describes results for the unemployment rate and then for the number of EI beneficiaries. In each case, the results are divided into the cross-correlation, the Granger causality, and the model. For the unemployment rate, we also present the sensitivity analysis.

a Unemployment Rate

i Cross-Correlation

The correlation between the Google index and the unemployment rate is stronger for past Google searches than for future ones. These results indicate that Google searches lead the unemployment rate. Table 2 shows the cross-correlation function for various lags of the Google index.

Table 2: Cross-Correlation Function Between the Unemployment Rate and the Google Index

h	-6	-5	-4	-3	-2	-1	0	1	2	3	4	5	6
CCF	0.4	0.4	0.39	0.37	0.36	0.33	0.3	0.27	0.21	0.18	0.14	0.09	0.05

Sources: Statistics Canada, Google Trends, Institute of Fiscal Studies and Democracy.
Notes: N=158, h=lag of Google index (in months), CCF=value of cross-correlation function. The values of the CCF tell the value of the correlation between the unemployment rate and lags of the Google index.

ii Granger Causality

Table 3 shows the results of the Granger causality test. The null hypothesis that the Google index does not Granger cause the unemployment rate can be rejected at the 1% level of confidence. Conversely, we do not reject that the unemployment rate does not Granger cause the Google index. This means the Google index should help in predicting the unemployment rate.

Table 3: Results of Granger Causality Test

	F-Value	P-Value
Google index does not Granger cause the unemployment rate	9.26	0.003**
The unemployment rate does not Granger cause the Google index	0.49	0.49

Sources: Statistics Canada, Google Trends, Institute of Fiscal Studies and Democracy.
Notes: N=158. Asterisks *,**,*** mark significance at the 5%, 1%, and 0.1% levels of confidence respectively of rejecting the hypothesis.

iii Model

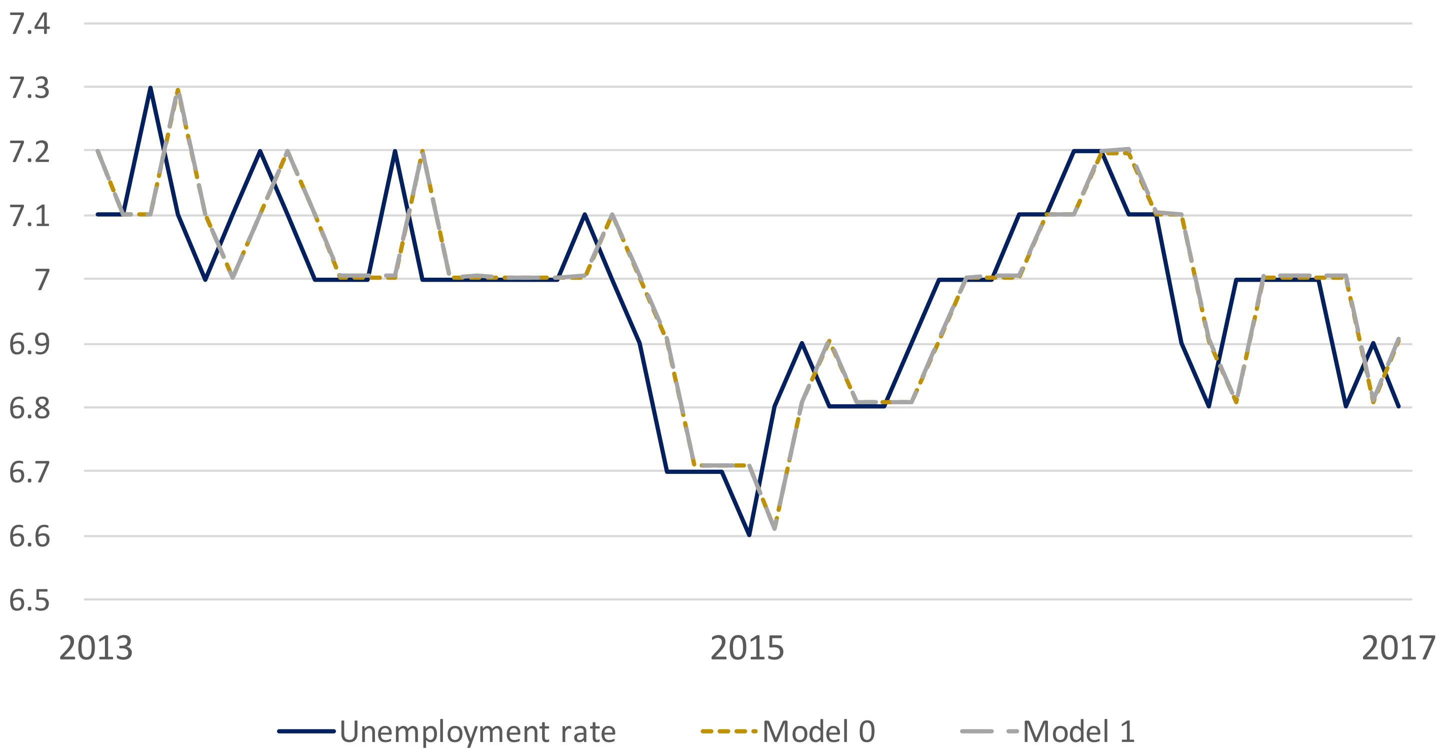
Table 4 gives the results of the estimation of Models 0 and 1. The coefficient of the Google index is 0.001, meaning that a 1 percent increase in searches leads to a 0.10% increase in the unemployment rate. This coefficient is statistically significant at the 5% level of confidence. The AIC for the extended model is only slightly smaller than the benchmark model, while the BIC is almost the same. The mean absolute percentage error is slightly higher. Chart 4 shows the one-step-ahead out-of-sample nowcasts of the unemployment rate. Chart 5 shows the evolution of the RMSE as new data are added over the 2010 to 2017 period for the benchmark and the extended model. We see that the extended model has a slightly smaller RMSE than the benchmark model, but overall the evolution for the RMSE is similar for both models.

Table 4: Estimation of Results of Benchmark AR(1) Model (Model 0) and the Extended Model (Model 1)

Variable	Model 0	Model 1
log (y_{t-1})	0.9720***	0.9736***
	(0.0158)	(0.0158)
X_t		0.001*
		(0.0005)
Constant	1.9501***	1.8842***
	(0.0487)	(0.0592)
Summary		
AIC	-770.77	-773.11
BIC	-761.74	-761.13
MAPE	0.7751	0.7821
n	158	158

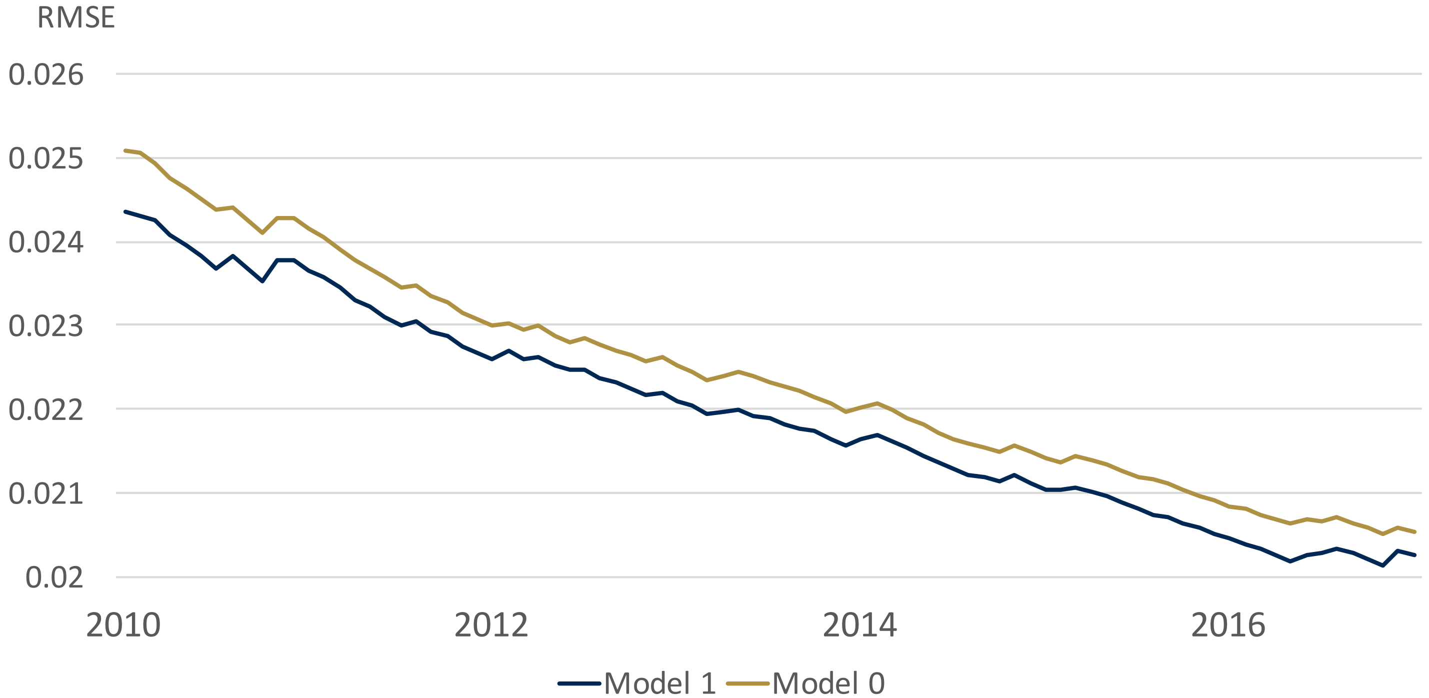
Sources: Statistics Canada, Google Trends, Institute of Fiscal Studies and Democracy.
Notes: Y=unemployment rate, x=Google index. Asterisks *,**,*** mark significance at the 5%, 1% and 0.1% level of confidence respectively.

Chart 4: Unemployment Rate 2013-2017 and the One-Step-Ahead Rolling Nowcasts for the Benchmark Model (Model 0) and the Extended Model (Model 1)



Sources: Statistics Canada, Google Trends Database, Institute of Fiscal Studies and Democracy.
Note: Seasonally adjusted.

Chart 5: Evolution of the RMSE as New Data Are Added Over the 2010-2017 Period for the Benchmark Model (Model 0) and the Extended Model (Model 1)



Sources: Statistics Canada, Google Trends Database, Institute of Fiscal Studies and Democracy.

iv Sensitivity Analysis

In this section, we vary the hypothesis of the model to understand how these impact the coefficient of the Google index. The results are presented in Table 5. Model 1 is the main model used in this paper. We test the impact of adding more decimals to the unemployment rate data, of using the Google index downloaded a week later than in the main model, of dropping the search terms EI login and EI benefits to add unemployment insurance to the Google index, of using data that is not seasonally adjusted, and of adding a seasonal term to the model using seasonally-unadjusted data. The rational of comparing a Google index downloaded a week later than in the main model is that the index values of the Google index seem to vary based on the date the Google index is downloaded.

We find that, for most models, the coefficient of the Google index is not statistically significant. In particular, when using Google index data downloaded a week later (Model 3), the coefficient of the Google index becomes not statistically significant. Combined with the fact that the coefficicent estimated for the Google index is very small and does not improve the model fit, we conclude that the Google index is not very useful in predicting the unemployment rate in Canada.

Table 5: Sensitivity Analysis Comparing Various Models

Model 1		
Variable	**Model 1.0**	**Model 1.1**
$\log(y_{t-1})$	0.9720***	0.9736***
	(0.0158)	(0.0158)
X_t		0.001*
		(0.0005)
Constant	1.9501***	1.8842***
	(0.0487)	(0.0592)
Model 2		
Variable	**Model 2.0**	**Model 2.1**
$\log(y_{t-1})$	0.9731***	0.9734***
	(0.0155)	(0.0155)
X_t		0.0005
		(0.0005)
Constant	1.9489***	1.9164***
	(0.0493)	(0.0588)
Model 3		
Variable	**Model 3.0**	**Model 3.1**
$\log(y_{t-1})$	0.9720***	0.9728***
	(0.0158)	(0.0159)
X_t		0.0007
		(0.0005)
Constant	1.9501***	1.9027***
	(0.0487)	(0.0589)
Model 4		
Variable	**Model 4.0**	**Model 4.1**
$\log(y_{t-1})$	0.9731***	0.9734***
	(0.0155)	(0.0155)
X_t		0.0005
		(0.0005)
Constant	1.9489***	1.9164***
	(0.0493)	(0.0588)

Table 5: Sensitivity Analysis Comparing Various Models (cont'd)

Model 5		
Variable	**Model 5.0**	**Model 5.1**
$\log(y_{t-1})$	0.9731***	0.9732***
	(0.0155)	(0.0155)
X_t		0.0001
		(0.0004)
Constant	1.9489***	1.9392***
	(0.0493)	(0.0575)
Model 6		
Variable	**Model 6.0**	**Model 6.1**
$\log(y_{t-1})$	0.7760***	0.7937***
	(0.0491)	(0.0485)
X_t		-0.0016
		(0.0010)
Constant	1.9459***	2.0551***
	(0.0253)	(0.0734)
Model 7		
Variable	**Model 7.0**	**Model 7.1**
$\log(y_{t-1})$	0.9720***	0.9728***
	(0.0158)	(0.0159)
$\log(Y_{t-12})$	0.9034***	0.9115***
	(0.0272)	(0.0258)
X_t		0.0012*
		(0.0006)
Constant	1.9445***	1.8615***
	(0.2435)	(0.2569)
Model 8		
Variable	**Model 8.0**	**Model 8.1**
$\log(y_{t-1})$	0.9352***	0.9348***
	(0.0238)	(0.024)
$\log(Y_{t-12})$	0.9050***	0.9132***
	(0.0268)	(0.0254)
X_t		0.0012*
		(0.0006)
Constant	1.9439***	1.8589***
	(0.2485)	(0.2621)

Table 5: Sensitivity Analysis Comparing Various Models (cont'd)

Model 9		
Variable	Model 9.0	Model 9.1
$\log(y_{t-1})$	0.9352***	0.9342***
	(0.0238)	(0.0241)
$\log(Y_{t-12})$	0.9050***	0.9082***
	(0.0268)	(0.0264)
X_t		0.0005
		(0.0005)
Constant	1.9439***	1.8884***
	(0.2485)	(0.2538)

Sources: Statistics Canada, Google Trends, Institute of Fiscal Studies and Democracy.
Notes: Y=unemployment rate, x=Google index. Asterisks *,**,*** mark significance at the 5%, 1%, and 0.1% level of confidence respectively. Model 1 is the main model included in the paper. Model 2 includes more decimals in the unemployment rate. Model 3 uses Google Trends data downloaded one week later than the main model presented in this paper. Model 4 includes more decimals in the unemployment rate and Google Trends data downloaded one week later than in the main model presented in this paper. Model 5 includes more decimals in the unemployment rate and Google Trends data downloaded one week later than the main model presented in this paper. Also, in this model the Google index is obtained including the term unemployment insurance and dropping EI login and EI benefits. Model 6 uses data that are not seasonally adjusted. Model 7 uses data that are not seasonally adjusted and includes a seasonal term. Model 8 uses data that are not seasonally adjusted, includes a seasonal term, includes more decimals for the unemployment rate, and uses Google Trends data downloaded one week later than the main model presented in this paper. Model 9 uses data that are not seasonally adjusted, includes a seasonal term, includes more decimals for the unemployment rate, and uses Google Trends data downloaded one week later than the main model presented in this paper using the term unemployment insurance and dropping EI login and EI benefits.

b EI Beneficiaries

i Cross-Correlation

The correlation between the Google index and the present number of EI beneficiaries is stronger for past Google searches than future ones. These results indicate that Google searches lead the number of EI beneficiaries. Table 6 shows the cross-correlation function for various lags of the Google index.

Table 6: Cross-Correlation Function Between the Number of EI Beneficiaries and the Google Index

h	-6	-5	-4	-3	-2	-1	0	1	2	3	4	5	6
CCF	0.42	0.43	0.43	0.42	0.42	0.39	0.36	0.32	0.28	0.23	0.17	0.13	0.07

Sources: Statistics Canada, Google Trends, Institute of Fiscal Studies and Democracy.
Notes: N=157, h=lag of Google index (in months), CCF=value of cross-correlation function. The values of the CCF tell the value of the correlation between the number of EI beneficiaries and lags of the Google index.

ii Granger Causality

Table 7 shows result of the Granger causality test. The null hypothesis that the Google index does not Granger cause the number of EI beneficiaries can be rejected at the 0.1% level of confidence. Conversely, we do not reject that the number of EI beneficiaries does not Granger cause the Google index. This means the Google index should help in predicting the number of EI beneficiaries.

Table 7: Results of Granger Causality Test

	F-Value	P-Value
Google index does not Granger cause the number of EI beneficiaries	18.28	<0.001***
The number of EI beneficiaries does not Granger cause the Google index	0.08	0.78

Sources: Statistics Canada, Google Trends, Institute of Fiscal Studies and Democracy.
Notes: N=157. Asterisks *,**,*** mark significance at the 5%, 1% and 0.1% levels of confidence respectively of rejecting the hypothesis.

iii Model

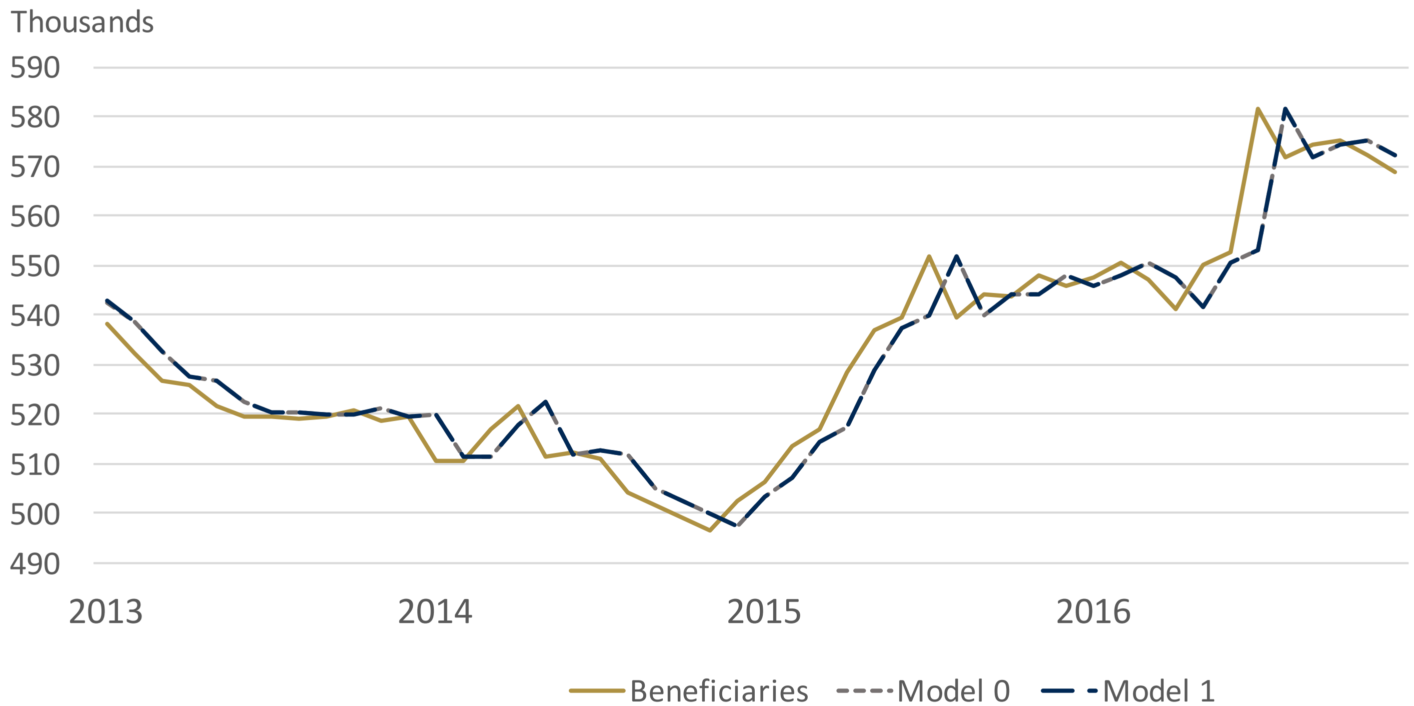
Table 8 shows the results of the estimation of models 1 and 2. The coefficient of the Google index is 0.0002, meaning that a 1% increase in searches leads to a 0.02% increase in the number of EI beneficiaries. However, this coefficient is not statistically significant. The AIC and BIC for the extended model are slightly higher than the benchmark model and the mean absolute percentage error is unchanged. Chart 6 shows the one-step-ahead out-of-sample nowcasts of the number of EI beneficiaries.

Table 8: Estimation of Results of the Benchmark AR(1) Model (Model 0) and the Extended Model (Model 1)

Variable	Model 0	Model 1
$\log(y_{t-1})$	0.9834***	0.9834***
	(0.0110)	(0.0110)
X_t		0.0002
		(0.0005)
Constant	13.2537***	13.2435***
	(0.0740)	(0.0804)
Summary		
AIC	-767.38	-765.65
BIC	-758.37	-753.43
MAPE	0.089	0.089
n	157	157

Sources: Statistics Canada, Google Trends, Institute of Fiscal Studies and Democracy.
Notes: Y=number of EI beneficiaries, x=Google index. Asterisks *,**,*** mark significance at the 5%, 1% and 0.1% levels of confidence respectively.

Chart 6: Number of EI Beneficiaries 2013-2017 and the One-Step-Ahead Rolling Nowcasts for the Benchmark Model (Model 0) and Extended Model (Model 1)



Sources: Statistics Canada, Institute of Fiscal Studies and Democracy.
Note: Seasonally adjusted.

V DISCUSSION AND CONCLUSION

We find that the Google index is correlated with the unemployment rate and the number of EI beneficiaries, and that the Google index is the leading variable in both cases. The results of a Granger Causality test show that the Google index anticipates these variables. We then build a simple AR(1) model to forecast the unemployment rate and another to forecast the number of EI beneficiaries.

In the case of the unemployment rate, we find that the coefficient of the Google index is statistically significant and that the extended model has a slightly smaller AIC, meaning that the overall fit of the model may be improved. However, results of the sensitivity analysis suggest that the Google index is not helpful in forecasting the unemployment rate. This result differs from that of Tuhkuri (2016a; 2016b) who found that the Google index had a significant but modest impact on the prediction of the unemployment rate in the United States and in Europe. The coefficient of the Google index was smaller in this case than what was found by Tuhkuri (2016b) in the United States. Tuhkuri (2016) found that the Google index decreases the mean absolute percentage error by 4.32% while we did not find a decrease in the mean absolute percentage error. However, the mean absolute percentage error of our model is smaller, indicating that our model may be slightly better at anticipating the unemployment rate in Canada than the model in the United States (Tuhkuri, 2016b).

In the case of the EI beneficiaries, we find that the coefficient of the Google index is almost equal to zero and is not statistically significant. We also find that extending the model with the Google index does not increase the fit of the model.

Our results suggest that the benchmark AR(1) model already predicts the unemployment rate quite well. It is surprising to note that the Google index did not have a statistically significant impact on the unemployment rate. The small coefficient of the Google index means that extending the model with this variable does not have a large impact on the prediction of the unemployment rate. However, the Google index may be more useful when there is a sudden change in the unemployment rate from one month to the next, perhaps from a recession or a boom in employment. If these lead to a change in the volume of employment insurance related searches, the Google index could anticipate the change in the unemployment rate better than the benchmark model. Future research should examine whether this is the case. Given that nowcasts of the unemployment rate would be especially useful to identify a recession or a boom, this could mean the Google index may be quite useful in the prediction of the unemployment rate when it counts most.

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