Real-time Indicators for Inflation and Economic Activity: A Natural Language Processing Approach*

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May 31, 2023

Abstract

This paper constructs new demand and supply indicators for Canada and United States using earnings call transcripts of publicly listed firms and Natural Language Processing techniques. The results show that the text-based indicators of demand/supply imbalance in the economy are highly correlated with both official output gap estimates and inflation data, pointing to a potential use for foreseeing inflationary pressures in the economy. Text-based business sentiment indicators comove with GDP growth in both countries. Moreover, these new indicators improve the accuracy of out-of-sample inflation and output forecasts. Examination of earnings calls around topics such as supply chain disruptions, labor shortages and capacity constraints highlights potential benefits of using the information in textual data to draw insights on a broad range of relevant issues in a timely manner. We conclude that the new measures based on earnings calls offer a promising candidate to the toolkit of policymakers.

Keywords: Output gap, Inflation forecast, GDP forecast, Natural Language Processing, Machine Learning, Demand sentiment, Supply sentiment, Business sentiment.
JEL Codes: C1; C3; E3; E5.

*Authors thank Fabio Canova, Justin Damien Guinette, Christopher Hajzler, Tolga Ozden, Nicolas Petrosky-Nadeau, Adam Hale Shapiro, Alexander Ueberfeldt, as well as seminar and conference participants at the Bank of Canada and 57^{th} Annual Meeting of the Canadian Economics Association for helpful discussions. The views expressed in this paper are solely those of the authors and may differ from official Bank of Canada views. No responsibility for them should be attributed to the Bank.

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1 Introduction

Monitoring aggregate demand and supply conditions in the economy is a key element of the conduct of monetary policy as it helps determine the degree of economic slack and associated inflationary pressures. Slack is typically measured by the output gap, i.e., the difference between the actual level of output and an estimated trend capturing the economy's productive capacity. This approach has important caveats since the estimated trend depends on the choice of methodology being used (e.g., filters, unobserved components, growth accounting) and is subject to significant revisions as new data comes in (Quast and Wolters, 2022; Canova, 2022; Champagne et al., 2018; Marcellino and Musso, 2011). This is shown to be an important factor in the evaluation and conduct of monetary policy (Coibion et al., 2018; Ng, 2018; Kozicki et al., 2004). Moreover, standard measures of economic slack fall short of explaining movements in inflation since the COVID-19 pandemic, a period during which both aggregate demand and supply were subject to large shocks (Faucher et al., 2022; Guerrieri et al., 2022; Ruch and Taskin, 2022).[1] This paper departs from standard output gap methodologies and presents an alternative indicator of economic slack using real-time transcripts of earnings calls of publicly traded Canada and United States firms. The proposed method provides more timely and direct measures of aggregate demand and supply conditions based on firm-level information, given that hard data for estimation of output gap is usually available with substantial lags. The earnings calls, on the other hand, are immediately available since they are held as public conferences. More importantly, the new measure from earnings calls captures inflationary pressures during the post-pandemic period where conventional slack measures are largely uninformative about inflation (e.g., Morley et al., 2023).

Earnings calls serve as an important communication channel between market par-

[1] See Ng and Wright (2013), Ng (2021), and Lenza and Primiceri (2022) for detailed discussions about the challenges for forecasting during episodes with large shocks such as the Great Recession and the COVID-19 pandemic.

ticipants and the management of publicly traded companies. They provide insights on companies' own outlook as well as their views around broader financial and economic developments. As such, public statements of corporate management teams could be used to draw insights on broad economic activity. In this paper, we extract information from earnings call transcripts of publicly listed companies in Canada and United States, covering the period between 2008Q1 and 2022Q4. To do so, we borrow from the natural language processing (NLP) methods. Our method relies on identifying demand and supply mentions in earnings call transcripts and measuring sentiment around those concepts in a similar fashion to Baker et al. (2016) and Hassan et al. (2021). More specifically, we measure sentiment (positive or negative) around demand and supply discussions. This method enables systematic quantitative analysis of large volumes of textual data which would otherwise be infeasible by reading and interpreting each individual transcript.

We then assess the usefulness of these indicators in a forecasting environment. Results show that our text-based estimate of economic slack tends to be highly correlated with the officially reported output gap estimates in normal times. However, there is a decoupling beginning in 2020. Specifically, since the beginning of the COVID-19 pandemic, the official output gap measures indicate a persistent state of excess supply. Our novel estimates, by contrast, points to a sharp transition between excess supply to excess demand in both Canada and United States that coincides with the emergence of global supply chain disruptions. This result is important for our ability to explain inflation since the pandemic: the text-based indicator provides more accurate forecasts of inflation. In addition, our estimate of slack is available to policymakers in real-time whereas traditional measures of the output gap are available with a delay given the two-month GDP publication lag in both countries as well as other major economies. Moreover, examination of earnings calls around other topics such as business sentiment, supply chain disruptions, labor shortages and capacity constraints point to potential benefits of using the information in textual data to draw insights on a broad range of relevant topics in a timely manner. We conclude that text-based measures of economic slack should be included in central banks' monitoring and forecasting toolkit.

This paper adjoins two major branches of research. First, our newly constructed demand and supply indicators draws from the recently expanding literature that applies NLP techniques to digital texts with economic content. For instance, Hassan et al. (2021) employ earnings call transcripts to estimate the impact of Brexit on publicly listed firms in the United Kingdom and across the world. Baker et al. (2016) construct an index for political uncertainty using newspaper articles and presents evidence on its impact on economic activity. Bybee et al. (2020) document the topics covered in economic news articles and show that real activity is significantly correlated with the weight of topics that reflect the state of the business cycle in the economy. Similarly, Manela and Moreira (2017) bring evidence on the link between news-based uncertainty and economic disasters using the textual information on front-pages of The Wall Street Journal between 1890 and 2007. Shapiro et al. (2022) build a news-based sentiment measure and show that it is predictive of movements of survey-based measures of consumer sentiment. Chen and Houle (2023) generate high-frequency and up-to-date indicators to monitor news media coverage of supply and labor shortages in Canada. Angelico et al. (2022) and Larsen et al. (2021) use text-based methods to construct consumers' inflation expectations.[2] We contribute to this strand of literature by constructing an output gap proxy by computing demand and supply sentiments using text-based methods from earning call transcripts and link those measures to other output gap estimates as well as inflation outcomes.

The second area of research to which we contribute is the empirical literature that quantifies economic slack and its role in forecasting inflation. Estimation of the output gap and discussion of its real-time properties are extensively covered in the literature (see Orphanides and Van Norden, 2005; Marcellino and Musso, 2011, for instance). A number of follow-up studies argue that conventional measures of the output gap are unreliable

[2]See Gentzkow et al. (2019) for a recent survey of research related to the use of text as data.

in real time because they commonly use trend estimation methods that are subject to large revisions at the end of the sample (see Cayen and Van Norden, 2005; Kamada, 2005; Cusinato et al., 2013, among others). We contribute to this literature by constructing a new proxy for the output gap and evaluate its usefulness in capturing inflationary pressures. Our method leverages direct discussions of "demand" and "supply" and does not depend on the methods of estimating unobserved trends in actual output data, making our approach robust to the commonly cited end point bias with traditional techniques. Moreover, the discussions in the earnings calls cover recent past and near future as well as the current state of the company and broader economy, providing a better picture of the short-term demand and supply conditions as compared to the trend estimation which likely overlooks short-term supply side developments. The rest of the paper is organized as follows. The next section describes the textual data set, elaborates our proxy for the output gap, and compares it with the relevant data for the Canadian economy. Section 3 uses the textual indicator in inflation forecasts and evaluates the comparative performance of the textual indicator in such forecasts, and section 4 concludes.

2 Constructing demand, supply and output gap indicators using textual data

In this section, we present our textual data set, describe the textual indicators of demand, supply, and output gap, and compare them with the relevant Canadian economic data.

2.1 Earnings calls data

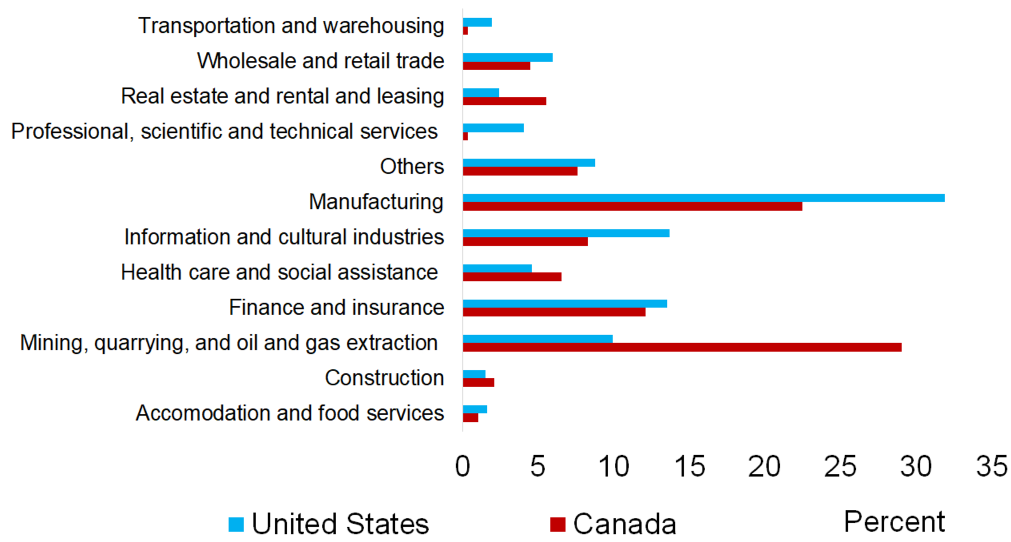
An earnings call is a quarterly press conference between the management of a public company, market participants, and the media to communicate the company's financial performance and discuss broader economic and financial developments. Given our macro focus, we are interested in assessing whether these calls contain helpful information about the economy beyond individual company performance. To do so, we leverage transcripts of earnings calls of publicly listed companies from Canada and United States.

Transcripts of earning calls are obtained from Seeking Alpha LLC, a financial data provider. We collect 115,668 available earning call transcripts from 2008Q1 to 2022Q4, of publicly traded companies headquartered in United States or Canada. The dataset covers a large number of earning calls from all major sectors (figure 1). This equates to over 7711 earning calls per year on average. Earnings calls from Canada and United States cover roughly 4 percent and 96 percent of the sample, respectively. The data covers all sectors with the most earning calls, about one-third, from manufacturing followed by Finance & Insurance and Information & Cultural Industries. Industry shares tend to be similar across the two countries although there is a greater representation of the Manufacturing in the United States and Mining, Oil Gas sectors Canada. When constructing time series from call-level data, we focus on 2013-2022 period for Canada because the earlier samples have relatively small observations.

We clean the raw data using NLP techniques to make it suitable for quantitative analysis. NLP is a field in machine learning that focuses on the interaction between computers and human language. The methods developed in this field aim to improve computers' ability to quantify textual data. The standard steps involved in preparing text for quantitative analysis include tokenization, lemmatization and removing stop words (Gentzkow et al., 2019).[3] Tokenization splits sentences into individual words (tokens) based on text delimiters such as spaces and commas. It is an important step in preparing data to be input into models because it converts text into a machine-readable format. Finally, we remove stop words from the tokenized text. The cleaning process is important not only to reduce the total number of unique terms in each document but also to arrive at a word count for each document that's comparable across earnings calls. After the cleaning process, the

[3]Stop words are frequently used functional words such as "the", "are", "and", "or", "in", "as", and so on. We used a common NLP library "stop-words" to identify stop words in the text. See https://pypi.org/project/stop-words/ for further details.

Figure 1: Sector distribution



Source: Authors' calculations, Seeking Alpha LLC.
Note: The figure plots sector distribution of earnings calls in 2022Q2. See text for further details.

textual data is used for quantitative analysis.

2.2 Quantifying demand and supply conditions

In this section, we describe the text mining techniques we use to construct our measures of demand and supply sentiment and then present the models we use to assess the usefulness of these indicators in a forecasting environment. We follow Hassan et al. (2021) in measuring sentimental variables in the pre-processed earnings call transcripts. Demand (supply) sentiment on a given call is obtained by aggregating sentiment scores around each mention of the word "demand" ("supply"). Sentiment is computed by the frequency of positive-tone terms minus negative-tone terms within the r-terms range of the mention, divided by the total number of words on the given call. More specifically, the sentiment score is calculated as follows:

$$Sentiment_{it}^{D,S} = \frac{1}{|B_{it}|} \sum_{b \in B_{it}} \left\{ \mathbf{1}^{\boldsymbol{D,S}}(b) \times \left(\sum_{c \in C^r(b)} S(c) \right) \right\}, \tag{1}$$

where B_it denotes the entire list of words in the call of firm i at time t, and $1^{D,S}(\cdot)$ is an indicator function which takes value 1 if the input word is in the "demand" ("supply") word list, and 0 otherwise. $C^r(b)$ denotes the set of words in the r-terms range of word b (before and after), and the function S(.) is defined as follows:[4]

$$S(c) = \begin{cases} +1 & \text{if } c \in S^+ \\ -1 & \text{if } c \in S^- \\ 0 & \text{otherwise,} \end{cases} \tag{2}$$

in which S^+ and S^- represent the lists of positive and negative tone words, respectively. The positive and negative keywords are identified using the Loughran and McDonald (2011) sentiment dictionary. These word lists contain finance-related sentiment text which allows us to identify the most relevant words for our purposes. The raw sentiment series are standardized (subtracted sample average and divided by sample standard deviation) to facilitate comparisons. Demand-supply imbalance is calculated by the difference between the standardized demand and supply sentiment scores. The entire process is conducted twice: one with the United States sample and another with the Canada sample.

2.3 Benchmarking textual indicators against hard data

In this subsection, we provide a descriptive summary of the constructed indicators and compare them with relevant data for the Canadian economy. Figure 2 plots the evolution of our demand and supply sentiment indicators over the sample period. While both series show relatively small variations over 2013-2019, large swings are observed post-2020. These

[4] We set r equal to 10 in the baseline calculations and repeating the same exercise by setting r equal 20 or 30 resulted in broadly similar results.

movements capture the commonly reported pandemic narrative: the contemporaneous collapse and rebound of demand and supply in 2020. This cycle is followed by a sharp decline in supply sentiment associated with the deterioration in global supply chains and increasing shortages of labor against a backdrop of resilient consumer demand in 2021.[5] An improvement in supply and an easing in demand conditions are observed in 2022.

Taking the difference between these two series yields our demand/supply imbalance (DS) indicator. Interestingly, movements in our DS measure are broadly consistent with the evolution of inflation over the sample period (figure 2). Inflation's decline in the initial phase of the pandemic as well as the sharp increase over the past two years is well reflected in the DS variable. The peak correlation between DS and inflation is .90 and occurs with a one quarter lag. As such, the fall in DS at the end of the sample indicates an impending period of disinflation.

Figure 3 compares our DS imbalance indicator with official output gap from Monetary Policy Reports of the Bank of Canada.[6] Two series move consistently over the sample period, with a substantial decoupling after the pandemic, pointing to different implications on post-Pandemic inflationary pressures.

3 Using textual indicators in inflation forecasts

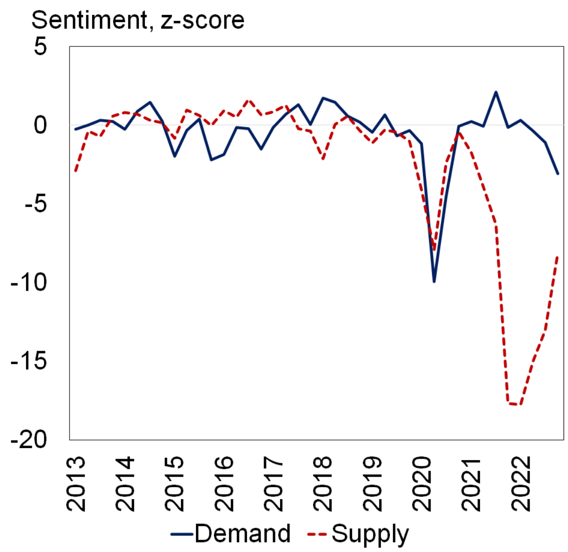
Given the promising descriptive results presented in the previous section, this section takes a formal approach to test the usefulness of the information content in the earnings calls in predicting inflation. For that purpose, we estimate commonly used parsimonious inflation forecast models and extend them with our textual indicators. Then, we compare the root mean squared forecast errors (RMSFEs) of out-of-sample forecasts of various models to assess the usefulness of the information in earnings calls.

[5] These narratives around supply chain disruptions and labor shortages are also corroborated by the increased frequency of discussions in earnings calls around these terms. The results are available in section 4.2.

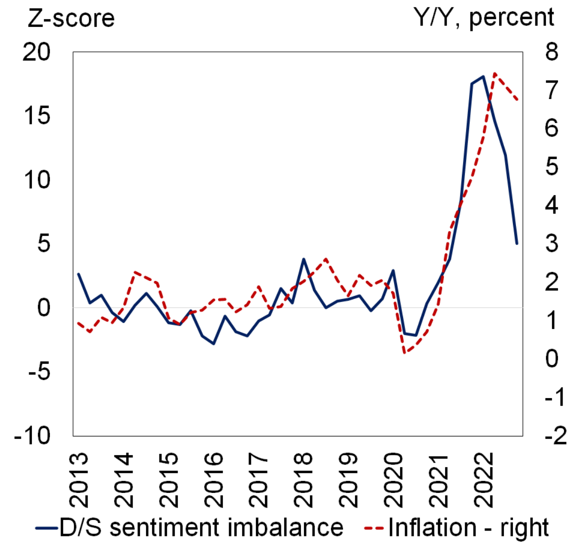
[6] See Pichette et al. (2015) for a detailed discussion of Bank of Canada's output gap calculations.

Figure 2: Demand/supply sentiments and inflation: Canada and United States

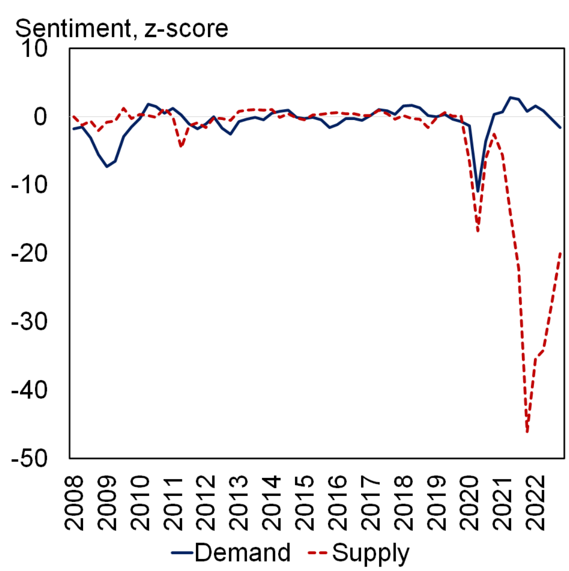
A. Demand and supply, Canada



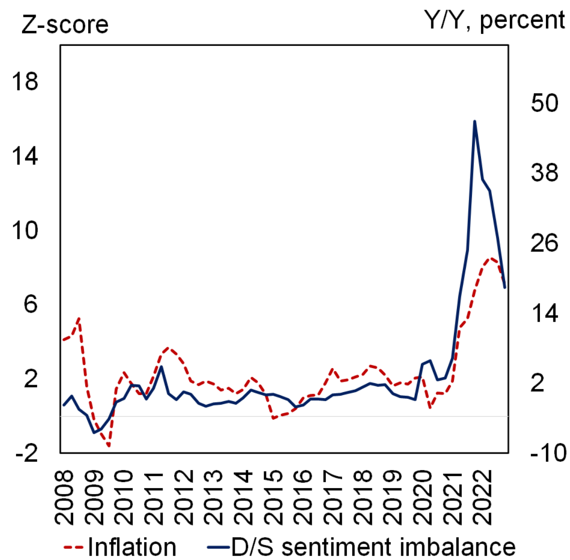
B. DS imbalance and inflation, Canada



C. Demand and supply, United States

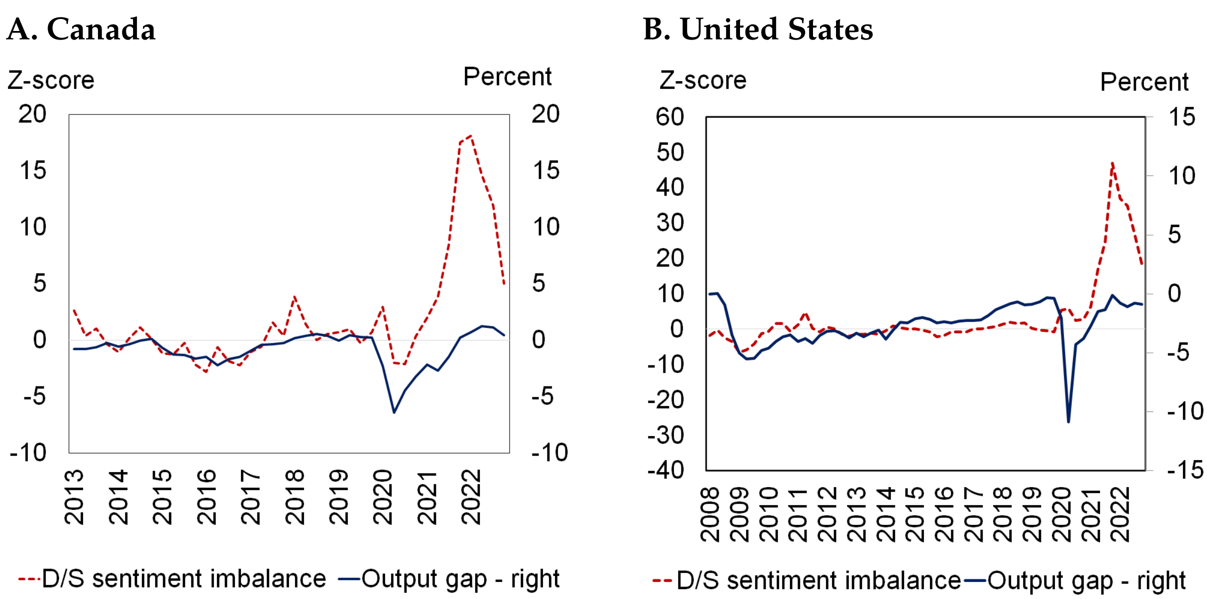


D. DS imbalance and inflation, United States



Source: Authors' calculations, Seeking Alpha LLC.
Note: Sentiment series are calculated as described in section 2.2. Inflation figures reflect year-over-year percent change in CPI series for both Canada and United States.

Figure 3: DS imbalance and output gap: Canada and United States



Source: Authors' calculations, Seeking Alpha LLC.
Note: Sentiment series are calculated as described in section 2.2. Output gap series reflect 2022Q4 vintages of Monetary Policy Report and Congressional Budget Office data for Canada and United States, respectively. See text for more details.

Using textual information in the forecasts is promising not only because of the strong correlation shown in the previous section, but also the timely information in the earnings calls. Hard data for estimation of output gap is usually available with substantial lags, however the earnings calls are immediately available in real-time. The information in the earnings calls can potentially improve our assessment of the current conditions of supply and demand, hence the output gap.

For Canada, the estimation and forecast periods cover 2013Q1-2019Q4 and 2020Q1-2023Q1, respectively. Given the short history of available text-based data, we divide the sample period as pre- and post-pandemic to assess the usefulness of our indicators during these unusual times. More specifically, we first estimate the models between 2013Q1 and 2019Q4 and generate a forecast for 2020Q1. We then iterate by rolling the estimation and forecast window one quarter forward. In the United States forecast exercises, we extend the sample back to 2008Q1 and repeat the same exercise.

In Canada forecasts, we use Monetary Policy Report output gap vintages for real-time estimates of economic slack. In the United States forecast, we used Congressional Budget Office's output gap vintages and linearly interpolated quarterly observations using biannual values, when needed.[7]

3.1 Forecast models

We use quarterly Canada and United States CPI inflation data to evaluate the performance of estimated forecast models. The following models are compared to assess to what extent our text-based demand and supply indicators improve accuracy of inflation forecasts.

[7] *The Green Book* output gap vintages for United States and the *Bank of Canada Staff Projections* are reported with several years of lag. Since we wanted to have post-COVID era in our analysis, we used the estimates of Congressional Budget Office for the United States, and the estimates in Monetary Policy Reports for Canada, available with much shorter lags.

- A benchmark univariate autoregressive model (AR):

$$\pi_t = \rho_0 + \sum_{i=1}^{k} \rho_i \pi_{t-i} + \epsilon_t. \quad (3)$$

This model is used as the benchmark case when comparing the performance of alternative models. Univariate models generate out-of-sample forecasts for inflation that are hard to improve upon (see for example Faust and Wright, 2009; Gospodinov and Ng, 2013; Champagne, Poulin-Bellisle and Sekkel, 2018).

- A generic Phillips Curve model with real time output gap (PC^{RT}):

$$\pi_t = \rho_0 + \sum_{i=1}^{k} \rho_i \pi_{t-i} + \gamma x_t^{RT} + \epsilon_t. \quad (4)$$

The variable x_t^{RT} represents the official real-time estimates of the output gap from Bank of Canada's monetary policy reports. We then use a Random Walk (RW) process for the gap for the out-of-sample dynamic simulations that generate the forecasts for π_{t+h}, where h is the horizon of the forecast in quarters.

- Previous model with final output gap (PC^F):

$$\pi_t = \rho_0 + \sum_{i=1}^{k} \rho_i \pi_{t-i} + \gamma x_t^F + \epsilon_t, \quad (5)$$

where x_t^F is the official final output gap estimate. This final estimate of the output gap is then used for the out-of-sample dynamic simulations that generate the forecasts for π_{t+h}, where again h is the horizon of the forecast in quarters.

- A model with textual output gap indicator (DS):

$$\pi_t = \rho_0 + \sum_{i=1}^{k} \rho_i \pi_{t-i} + \gamma z_t + \epsilon_t. \quad (6)$$

Table 1: Inflation forecasts (year-over-year)

RMSFE ratio relative to AR	Canada (1) PC^{RT}	(2) PC^{F}	(3) DS	United States (4) PC^{RT}	(5) PC^{F}	(6) DS
T0	1.117	1.077	0.777	0.964	0.900	0.811
T1	1.167	1.068	0.615	0.965	0.936	0.535
T2	1.166	1.026	0.51	0.979	0.923	0.517
T3	1.170	0.992	0.652	1.009	0.927	0.57
T4	1.188	0.962	0.812	1.038	0.921	0.611

Notes: Columns (1), (2), and (3) show RMSFEs of the corresponding model forecasts relative to the baseline model. AR: Autoregressive model, PC^{RT}: Phillips Curve with the official Real Time output gap, PC^{F}: Phillips Curve with the official Final output gap, DS: model with Demand/Supply imbalance indicator. Official output gap series reflect Monetary Policy Report figures for Canada and Congressional Budget Office (CBO) figures for United States. See text for more details.

Variable z_t represents the demand/supply proxy of the output gap from earnings calls transcripts, constructed in this paper. We then use a RW process of the demand/supply imbalance proxy for the out-of-sample dynamic simulations that generate the forecasts for π_{t+h}, where h is the horizon of the forecast in quarters.

3.2 Forecast performance

Table 1 shows the baseline forecast performance results. The RMSFEs of the three alternative models for the current quarter nowcast (T0), and for the following one, two, three, and four quarters ahead horizons are reported relative to the benchmark model (AR). Several interesting results emerge from the forecast exercises. The model with demand/supply indicator (DS) outperforms both the baseline model and the two reference PC models. It proves the usefulness of the timely information content in the earnings calls beyond the descriptive correlations presented in the previous section. The RMSFE gains remain positive over the entire forecast horizon up to four quarters. This is true for both Canada and United States.

Another finding is that the model with final output gap (PC^{F}) performs better than the model with real-time output gap (PC^{RT}), in line with the previous results covering earlier periods and various countries in the literature (e.g., Orphanides and Van Norden, 2005). The PC^{RT} model underperforms the univariate autoregressive model, confirming the earlier results from Champagne, Poulin-Bellisle and Sekkel (2018) for Canada and Faust et al. (2013) for United States. The comparison of PC^{F} with the AR returns mixed results, with these models beating each other over different time horizons. We test the robustness of the empirical results in the next section.

3.3 Robustness

As described above, for the out-of-sample dynamic simulations of x_t^{RT} and z_t over the forecast horizons, we use a RW process in the benchmark case. Moreover, we assumed quarterly inflation at time t is unknown and therefore nowcasted as described in section 3. We pursue two directions and relax the aforementioned assumptions to assess the robustness of our results. First, we use alternative models to simulate dynamic out-of-sample values for x_t^{RT} and z_t. Second, we relax the assumption that quarterly inflation is unknown at quarter t and adopted alternative information structures.

The following alternative models are used to generate out-of-sample dynamic simulations for the predictive variables.

- Autoregressive process ($AR1$): This model simply takes x_{t-1} as the forecast for the x_{t+h}, where h represents forecast horizon.[8]

- An alternative AR model for each forecast horizon (ALT):

$$x_t = \rho_0^h + \ \rho_1^h x_{t-h} + \epsilon_t^h, \tag{7}$$

[8]Given the short sample we have due to the availability of textual data, we focus on AR(1), that is $k = 1$.

for each forecast horizon h. This model uses the latest available inflation value in all forecast horizons with different coefficients estimated in the equations described above.[9]

Next, we relax the assumption about the available information in each quarter t.[10] The benchmark case assumed that π_t was unknown during quarter t and nowcasted using the information up to $t-1$. In fact, in the end of quarter t, first two months' inflation of the quarter are observed. In the following alternatives, we use this information and proceed with the forecasts accordingly.

- Shift monthly CPI series one period back (SHIFT) for each t in the forecast window:

$$P_t^{SHIFT} = \frac{1}{3}\left[P_t^{m1} + P_t^{m2} + P_{t-1}^{m3}\right]. \tag{8}$$

  In this case, actual price level at quarter t is assumed to be equal to the price level calculated by the shifted price series, P_t^{SHIFT}. In equation (9), term P_t^{mk} denotes the CPI level in k^{th} month of quarter t.

- Take average of the available two months $(2M)$:

$$P_t^{2M} = \frac{1}{2}\left[P_t^{m1} + P_t^{m2}\right]. \tag{9}$$

  In this case, actual price at quarter t is assumed to be equal to the average of the first two months' observations, again with the term P_t^{mk} denoting the CPI level in k^{th} month of quarter t.

- Assume price level is known and equals the actual historical value in quarter t (KNOWN).

[9] See Gosselin and Tkacz (2001) for a detailed discussion on this model.

[10] We thank Fabio Canova for suggesting these alternative information structures in the forecast exercises.

Table 2: Robustness: Inflation forecasts (year-over-year)

RMSFE ratio relative to AR	BASELINE (1) PC^{RT}	(2) PC^{F}	(3) DS	ALT (4) PC^{RT}	(5) DS	AR1 (6) PC^{RT}	(7) DS
BASELINE							
T1	1.167	1.068	0.615	1.155	0.718	1.155	0.718
T2	1.166	1.026	0.51	1.133	0.631	1.143	0.681
T3	1.17	0.992	0.652	1.106	0.823	1.134	0.962
T4	1.188	0.962	0.812	1.075	0.979	1.132	0.934
SHIFTED							
T1	1.298	1.184	0.673	1.28	0.782	1.28	0.782
T2	1.246	1.084	0.574	1.206	0.704	1.218	0.745
T3	1.213	1.022	0.687	1.144	0.869	1.174	1.005
T4	1.201	0.973	0.825	1.088	0.993	1.146	0.947
2M							
T1	1.35	1.229	0.666	1.331	0.784	1.331	0.784
T2	1.272	1.105	0.577	1.231	0.709	1.244	0.754
T3	1.226	1.032	0.691	1.156	0.873	1.186	1.012
T4	1.207	0.978	0.827	1.093	0.996	1.151	0.95
KNOWN							
T1	1.395	1.262	0.665	1.374	0.805	1.374	0.805
T2	1.288	1.115	0.582	1.246	0.723	1.259	0.769
T3	1.232	1.037	0.693	1.162	0.877	1.192	1.018
T4	1.211	0.981	0.829	1.097	0.998	1.155	0.952

Notes: RMSFEs are reported relative to the baseline model. AR: Autoregressive, PC^{RT}: Phillips Curve with the official Real Time output gap, PC^{F}: Phillips Curve with the official Final output gap, DS: model with Demand/Supply imbalance indicator. Official output gap series reflect Monetary Policy Report figures for Canada and Congressional Budget Office (CBO) figures for United States. See text for more details.

In these alternative information structures, since inflation at quarter t is assumed to be equal to the described alternatives, nowcast is naturally omitted. Inflation is forecasted for horizons 1 to 4 as described in section 3.1 (PC^{RT}, PC^{F}, DS).

The results with alternative assumptions are presented in Tables 2 and 3 for Canada and United States, respectively. The robustness exercises return broadly similar results with the ones under baseline assumptions. As long as the right-hand-side variables are treated consistently, the improvement of forecast accuracy with our newly constructed variable holds, pointing to usefulness of information in timely earnings calls.

Table 3: Robustness: Inflation forecasts (year-over-year)

RMSFE ratio relative to AR	BASELINE (1) PC^{RT}	(2) PC^{F}	(3) DS	ALT (4) PC^{RT}	(5) DS	AR1 (6) PC^{RT}	(7) DS
BASELINE							
T1	0.965	0.936	0.535	0.965	0.727	0.965	0.727
T2	0.979	0.923	0.517	0.978	0.858	0.977	1.041
T3	1.009	0.927	0.57	1.001	0.888	1	1.618
T4	1.038	0.921	0.611	1.02	0.731	1.017	0.87
SHIFTED							
T1	0.986	0.955	0.531	0.986	0.755	0.986	0.755
T2	0.996	0.941	0.532	0.993	0.923	0.992	1.126
T3	1.018	0.931	0.59	1.01	0.933	1.008	1.709
T4	1.042	0.919	0.629	1.023	0.757	1.02	0.89
2M							
T1	0.988	0.956	0.527	0.988	0.801	0.988	0.801
T2	0.999	0.941	0.528	0.995	0.947	0.994	1.158
T3	1.02	0.931	0.588	1.011	0.942	1.009	1.734
T4	1.043	0.919	0.628	1.024	0.757	1.021	0.892
KNOWN							
T1	0.99	0.955	0.529	0.989	0.844	0.989	0.844
T2	1.001	0.942	0.531	0.997	0.971	0.996	1.188
T3	1.022	0.932	0.59	1.013	0.951	1.011	1.757
T4	1.044	0.92	0.628	1.025	0.758	1.023	0.896

Notes: RMSFEs are reported relative to the baseline model. AR: Autoregressive, PC^{RT}: Phillips Curve with the official Real Time output gap, PC^{F}: Phillips Curve with the official Final output gap, DS: model with Demand/Supply imbalance indicator. Official output gap series reflect Monetary Policy Report figures for Canada and Congressional Budget Office (CBO) figures for United States. See text for more details.

Table 4: Inflation shocks and DS indicator

	(1) π shock (LENS-CA)	(2) π shocks (TOTEM-CA)	(3) π shocks (MUSE-US)
DS indicator	0.00019*	0.00184**	0.00037***
	(0.000)	(0.001)	(0.000)
Constant	-0.00027	-0.00007	-0.00045
	(0.000)	(0.002)	(0.001)
Observations	40	40	60
R-squared	0.14	0.38	0.14

Notes: Note: Robust standard errors in parentheses. *, * and *** represent statistical significance at the 10%, 5% and 1% levels, respectively. LENS-CA: Large Empirical and Semi-structural Model for the Canadian economy, TOTEM-CA: the Terms-of-trade Economic Model for the Canadian economy. MUSE-US: Model of the United States Economy. See text for more details.

3.4 DS indicator and inflation shocks in large-scale models

In the previous section, we evaluated the significance of information provided in earnings calls compared to pre-existing forecast models. Central banks use their own extensive models for projecting economic outcomes. To determine if our textual indicators can enhance these large-scale models' forecasts, we analyze the inflation shocks derived from the macroeconomic models of the Bank of Canada for both Canada and the United States.

There are two baseline macroeconomic models for Canada, the Large Empirical and Semi-structural Model (LENS; Gervais and Gosselin, 2014) and the Terms-of-trade Economic Model (TOTEM; Corrigan et al., 2021), and one large-scale model for the economy of the United States, Model of the United States Economy (MUSE; Gosselin and Lalonde, 2005). We run the DS indicator on shock series to inspect whether our series capture some of the variation in inflation that remains unexplained within the Bank's macroeconomic models.

Table 4 reports the estimated coefficients of DS indicator in the inflation shock regressions. As shown in the table, the DS variable is statistically significant and the regression captures substantial shares of variation in inflation shocks, pointing to potential benefits of using our series in large-scale macroeconomic models of inflation forecasts.

4 Other potential uses of earnings calls

While the primary focus of the paper is using earnings calls for drawing insights on output gap and inflationary pressures, here we provide an extension section to discuss other potential benefits of using earnings calls to shed light on future research directions. Specifically, we construct a new business sentiment index and show that it is helpful in GDP growth forecasts. Moreover, discussions around topical issues such as global supply chains, capacity constraints and labor market shortages bring timely insights about these topics, broadly consistent with the commonly reported narratives around these topics.

4.1 Aggregate business sentiment

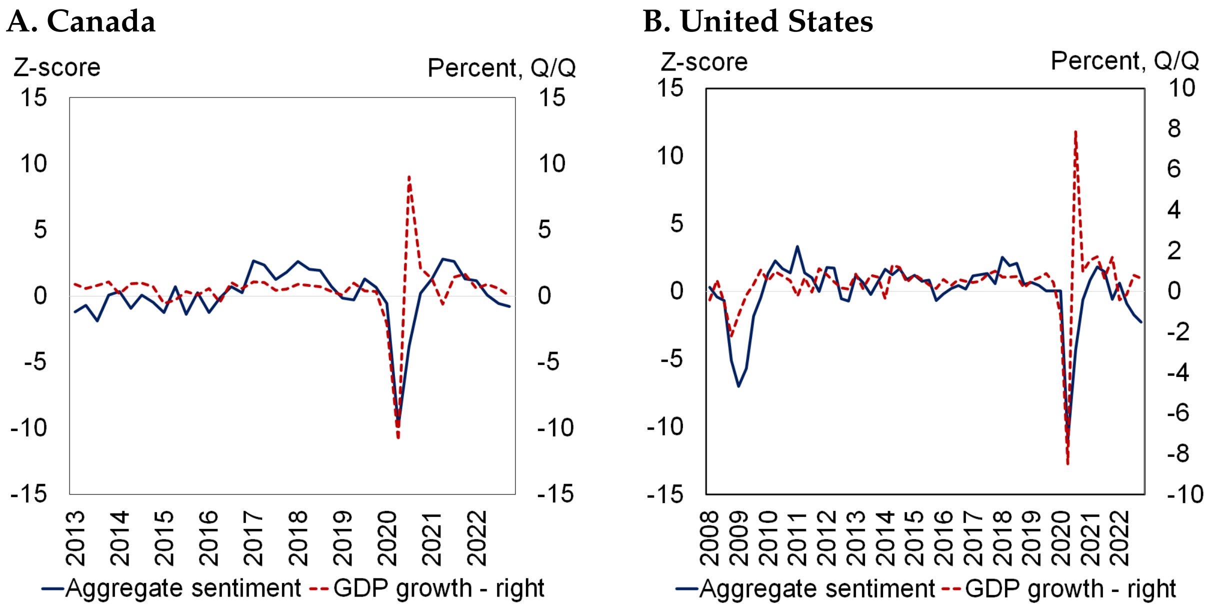
We define aggregate business sentiment using a modified version of equation (1). In this case, we compute the sentiment in the entire earnings call text instead of focusing on particular terms such as "demand" and "supply", in order to capture business sentiment in a broader context. More specifically, the aggregate business sentiment is defined as follows:

$$Sentiment_{it}^{B} = \frac{1}{|B_{it}|} \sum_{b \in B_{it}} S\left(b\right), \tag{10}$$

where B_it denotes the entire list of words in the call of firm i at time t. The definition of $S(\cdot)$ and the rest of the calculations follow section 2.2.

Figure 4 shows that aggregate business sentiment series are well-aligned with GDP growth in both Canada and United States. Next, we use the new business sentiment series to assess the value of information in forecasting economic activity. For that purpose, we estimate commonly used parsimonious GDP forecast models and extend them with our

Figure 4: Aggregate business sentiment and GDP growth: Canada and United States



Source: Authors' calculations, Haver Analytics, Seeking Alpha LLC.
Note: Sentiment scores are calculated using the methodology presented in section 2.2. GDP series reflect constant prices for both Canada and United States. See text for further details.

textual indicators. Then, we compare the RMSFEs of out-of-sample forecasts of various models to assess the usefulness of the information in earnings calls.

For Canada, the estimation and forecast periods cover 2013Q1-2019Q4 and 2020Q1-2023Q1, respectively. Given the short history of available text-based data, we divide the sample period as pre- and post-pandemic to assess the usefulness of our indicators during these unusual times. More specifically, we first estimate the models between 2013Q1 and 2019Q4 and generate a forecast for 2020Q1. We then iterate by rolling the estimation and forecast window one quarter forward. In the United States forecast exercises, we extend the sample back to 2008Q1 and repeat the same exercise.

We use quarterly GDP data of Canada and United States to evaluate the performance of forecast models. The following models are compared to assess to what extent our text-based business sentiment indicator improve accuracy of GDP growth forecasts.

- A benchmark univariate autoregressive model (AR):

$$y_t = \rho_0 + \sum_{i=1}^{k} \rho_i y_{t-i} + \epsilon_t. \tag{11}$$

  This model is used as the benchmark case when comparing the performance of alternative models.[11]

- A model with textual business sentiment indicator (B):

$$y_t = \rho_0 + \sum_{i=1}^{k} \rho_i y_{t-i} + \gamma z_t + \epsilon_t. \tag{12}$$

  The variable z_t represents the business sentiment indicator from earnings calls transcripts. We then use a RW process for the business sentiment series for the out-of-sample dynamic simulations that generate the forecasts for y_{t+h}, where h is the horizon of the forecast in quarters.

- A model with textual output gap indicator (DS):

$$y_t = \rho_0 + \sum_{i=1}^{k} \rho_i y_{t-i} + \gamma z_t + \epsilon_t. \tag{13}$$

  The variable z_t represents the demand/supply proxy of the output gap from earnings calls transcripts. We use a RW process for the demand/supply imbalance proxy for the out-of-sample dynamic simulations that generate the forecasts for y_{t+h}, where h is the horizon of the forecast in quarters.

- A model with both business sentiment and textual output gap indicator (B-DS):

$$y_t = \rho_0 + \sum_{i=1}^{k} \rho_i y_{t-i} + \gamma z_t + \lambda x_t + \epsilon_t. \tag{14}$$

[11]Given the short sample we have due to the availability of textual data, we focus on AR(1), that is $k = 1$.

Table 5: GDP forecasts (q-over-q), Canada

RMSFE ratio relative to AR	BASELINE (1) B	(2) DS	(3) B-DS	ALT (4) B	(5) DS	(6) B-DS	AR1 (7) B	(8) DS	(9) B-DS
T0	0.805	1.003	0.823	0.805	1.003	0.823	0.805	1.003	0.823
T1	0.505	1.006	0.515	0.505	1.006	0.515	0.512	1.006	0.515
T2	0.328	1.011	0.339	0.33	1.011	0.338	0.336	1.01	0.341
T3	0.217	1.015	0.225	0.218	1.015	0.225	0.224	1.014	0.229
T4	0.147	1.019	0.153	0.148	1.019	0.154	0.152	1.018	0.157

item Notes: RMSFEs of the corresponding model forecasts are reported relative to the baseline model. See text in section 4.1 for definitions.

Variable z_t and x_t represent the demand/supply indicator and business sentiment from earnings calls transcripts. We use RW processes for the demand/supply indicator and business entiment for the out-of-sample dynamic simulations that generate the forecasts for y_{t+h}, where h is the horizon of the forecast in quarters.

Tables 5 and 6 show the baseline forecast performance results. The RMSFEs of the three alternative models for the current quarter nowcast (T0), and for the following one, two, three, and four quarters ahead horizons are reported relative to the benchmark model (AR). In both United States and Canada forecasts, the model with business sentiment indicator (B) outperforms the baseline model and two other models with demand/supply indicator (DS, B-DS) as a predictive variable. In GDP forecasts, the relatively higher predictive power of the aggregate business sentiment indicator compared to the DS indicator can be attributed to the more comprehensive representation of discussions on overall economic activity throughout the entire earnings call. This is in contrast to focusing solely on specific terms such as demand and supply. The RMSFE gains are positive over the entire forecast horizon up to four quarters.

As described above, for the out-of-sample dynamic simulations of x_t and z_t over the forecast horizons, we use an RW process in the benchmark case. We repeated the same robustness exercises presented in section 3.3 and present them in columns (4) to (9) in

Table 6: GDP forecasts (q-over-q), United States

	BASELINE			ALT			AR1		
RMSFE ratio	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
relative to AR	B	DS	B-DS	B	DS	B-DS	B	DS	B-DS
T0	0.735	1.183	0.82	0.735	1.183	0.82	0.735	1.183	0.82
T1	0.665	1.547	0.811	0.665	1.547	0.811	0.687	1.557	0.802
T2	0.419	2.164	0.796	0.42	2.156	0.7	0.433	2.206	0.708
T3	0.282	2.764	0.776	0.287	2.755	0.531	0.335	2.847	0.527
T4	0.281	3.691	0.605	0.278	3.674	0.521	0.308	3.833	0.56

Notes: RMSFEs of the corresponding model forecasts are reported relative to the baseline model. See text in section 4.1 for definitions.

Tables 5 and 6. The RMSFE gains remain substantial under these alternative models for both Canada and United States.

4.2 Descriptive evidence on selected topics

The economic recovery after the COVID-19 pandemic exhibited several notable phenomena across major economies. Some of these phenomena, such as the inflation surge across a broad spectrum of major economies, were shared by the United States and Canada, and sparked intense discussions among academics and policymakers. The inflation surge was driven by various factors, including labor market shortages, global supply disruptions, and capacity constraints, among others (Agarwal and Kimball, 2022). Given the prominence of these topics in the policy debate over the past three years, we present descriptive evidence on these issues to explore whether earnings calls could offer timely information for policymakers. Specifically, we calculate discussion intensity of some of the highlighted topics and examine their evolution, with an emphasis on the post-COVID era.

Figure 5 illustrates the discussion intensity of labor shortages, supply disruptions, and capacity constraints on the earnings calls–measured as the average mentions per call. Discussions around supply chain disruptions and capacity constraints, for instance, intensified sharply during the post-COVID recovery in economic activity in both Canada and United States. This is in line with the commonly reported narrative that is supported by indicators such as suppliers' delivery times, order backlogs, and increased shipping costs (LaBelle and Santacreu, 2022; Benigno et al., 2022).

The degree of slack in the labor market of United States and Canada has also been widely discussed recently, amid wage-inflation spiral concerns. Labor market tightness, indeed, has been a major factor in monetary policy decisions in these countries, evident in the press conferences of the central banks. The elevated rates of vacancy over unemployed ratios during the post-COVID era coincided with a sharp increase in the intensity of discussions around labor shortages in earnings calls.[12] The comovement between the hard data related to the highlighted topics and the preliminary indicators in the earnings calls point to useful and timely information in these calls, that can be used to draw timely insights on a broad range of topics relevant for policymakers.

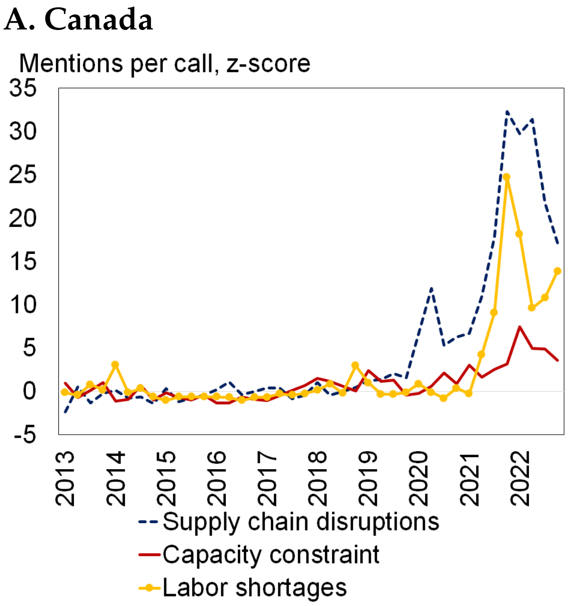
We finally illustrate the intensity of recession discussions alongside business sentiment in earnings calls. The strong negative correlation between these two series is noteworthy and common in both countries. These indicators could be used to anticipate the overall economic conditions as shown by Bybee et al. (2020) in the context of sentiment in business news articles.

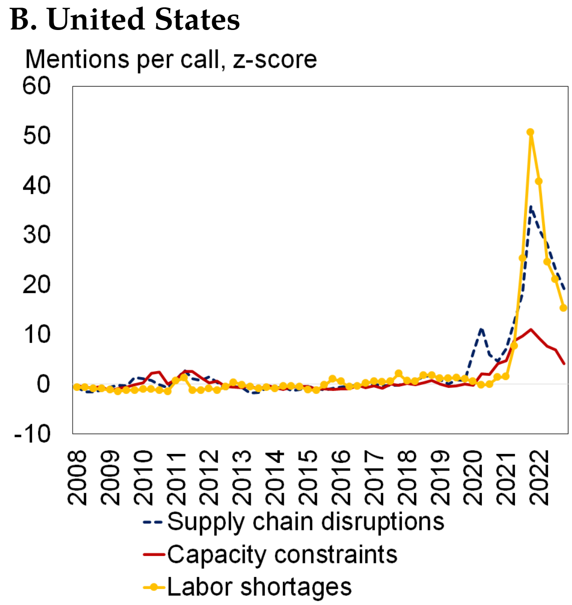
5 Conclusion

The output gap, a key concept for monetary policy, refers to the discrepancy between the level of actual output and an estimated level that captures the economy's potential. The traditional methods for estimation of the potential as a trend are subject to considerable adjustments as new data is received, therefore come with important drawbacks. These measures also fell short of anticipating the sharp acceleration in prices during the post-COVID era. In contrast to conventional output gap approaches, this paper proposes an

[12]See Domash and Summers (2022) and Ens et al. (2021) for extensive discussions on labor market tightness in the United States and Canada, respectively.

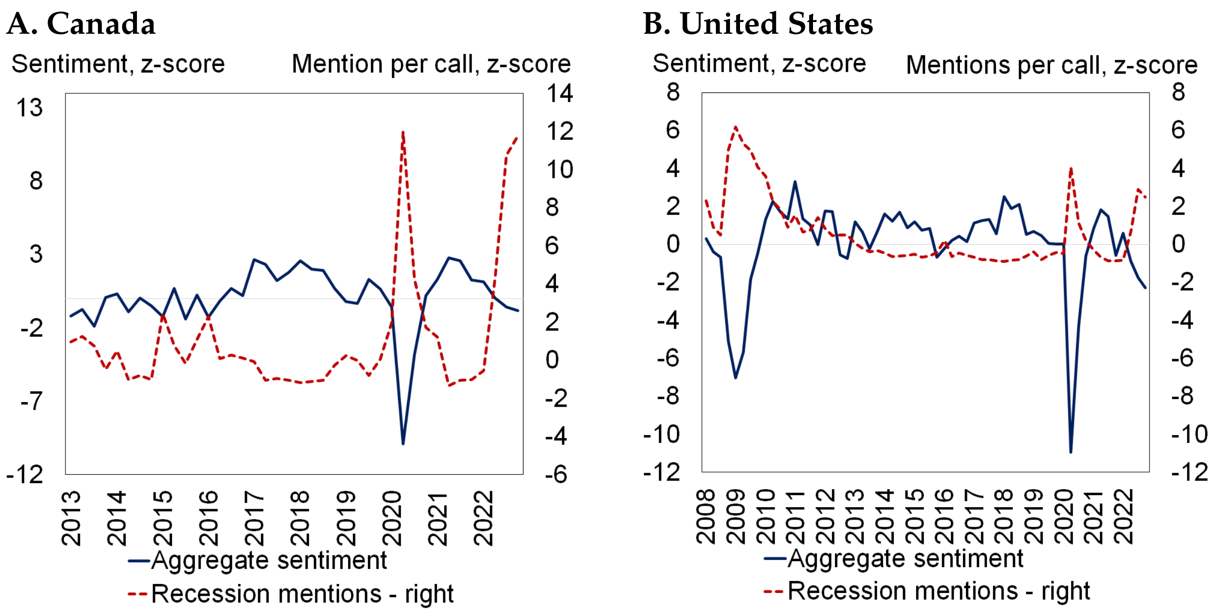
Figure 5: Supply chain disruptions, capacity constraints, and labor shortages





Source: Authors' calculations, Seeking Allpha LLC.
Note: Mention per call calculation employs the following methodology. In each call, we identify the number of mentions of a given term by identifying the keywords related to the given term, add the number of mentions of each keyword and divide by the total number of words in the given call. Aggregate time series are computed as simple average across calls in each quarter. The following keyword lists are used as the baseline case in the figure: supply chain disruption: "supply chain, supply disruption, supply bottleneck", labor shortage: "labor shortage, staff shortage, ", capacity constraint: "capacity constraint, production constraint, supply constraint". The supply chain disruption keyword list is extended with "logistic constraint, logistic disruption, supply shortage, component shortage, chip shortage, semiconductor shortage, input shortage, container shortage, driver shortage, part shortage, product shortage, inventory shortage, ship shortage", and the labor shortage keyword list is extended with "employee shortage, skill shortage, workforce shortage", and the evolution of the time series remained broadly similar. See text for further details.

Figure 6: Aggregate business sentiment and recession discussions



Source: Authors' calculations, Seeking Alpha LLC.
Note: Mention per call calculation employs the following methodology. In each call, we identify the number of mentions of a given term by identifying the keywords related to the given term, add the number of mentions of each keyword and divide by the total number of words in the given call. Aggregate time series are computed as simple average across calls in each quarter. The following keyword lists are used as the baseline case in the figure. Recession: "recession, recessionary". The recession keyword list is extended with "economic uncertainty, economic crisis, economic downturn, financial crisis, weak economy, economic slowdown, economic turmoil" and the evolution of the time series remained broadly similar. The aggregate sentiment calculation employs the methodology presented in section 4.1. See text for further details.

alternative approach to proxy output gap or economic slack using text analytics.

We construct new demand and supply indicators for the Canadian economy by text mining earnings call transcripts. The findings indicate a potential signalling role for inflationary pressures in the economy as the text-based indicators of demand/supply imbalance are substantially linked with both official output gap estimates and inflation data. Additionally, using these new variables to forecast inflation improves prediction accuracy. Moreover, preliminary examination of earnings calls around other topics such as supply chain disruptions, labor shortages, and capacity constraints point to potential benefits of using the information in textual data to draw insights on a broad range of relevant topics in a timely manner. Detailed analysis of further topical issues are left for future research.

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Appendix A. Sample excerpts from selected earning calls

Ford Motor Co., October 29, 2020
Looking at North America, despite the **difficult** backdrop of **COVID**, the Ford team executed well operationally. We optimize incentives for lower dealer stock levels, we maximize production and skillfully manage **supply** chains to meet **stronger-than-expected** customer **demand**. Now that margin was driven largely by higher-than-expected vehicle **demand**, positive net pricing and favorable mix as inventories were limited because of the **virus**-related **shutdowns** in the first half of the year. North America and China benefited from growth in both wholesales and revenue, while Europe, South America and our international's market group were still affected by **COVID**-related industry declines.
Zoom Video Communications Inc., June 3, 2020
Let me share some metrics that illustrate the **demand** we experienced in this past quarter. Customers with more than 10 employees grew 354% year-over-year, as we deployed millions of licenses for new customers in the quarter. As our **demand** increased and we had limited visibility into the growth, AWS was able to respond quickly by provisioning the majority of the new servers we needed, so sometimes adding several thousands a day for several days in a row. We are grateful for the incredible increase in **demand** as millions of doctors and patients, teachers and students, businesses and consumers chose Zoom to deliver critical communication and connection in a time of need. It speaks greatly of their trust and the quality and ease-of-use of our technology platform. We are also proud of our efforts to support our customers, employees and the global community during the **COVID**-19 **pandemic**.
Advanced Micro Devices Inc., April 29, 2020
Although there are some near-term uncertainties in the **demand** environment, we are well-positioned to navigate through this situation. We have a **solid financial foundation** and our product portfolio is very well positioned across the PC, gaming and data center markets. While **demand** indicators across commercial, education and data center infrastructure markets are strong, we expect some softness in consumer **demand** in the second-half of the year depending on how overall **macroeconomic conditions** evolve. I'm pleased with our execution in the quarter, as we quickly adopted our global operations to navigate pockets of **supply chain disruption** and addressed geographic and market **demand** shifts caused by **COVID**-19. We saw some **softness** based on the **COVID**-19 situation in China that impacted PC-related sales in the first quarter.

Source: Seeking Alpha LLC.

Canadian Tire, May 12, 2022

We continue to see **healthy demand** signals... There's no question we continue to operate in an environment where inflation is real, and **global supply chains** continue to be challenged.

As we look forward, here, we've had a late start to spring, but through what we're looking at, the **demand signals** are still pretty **strong**.

As for cargo, a **high demand** for cargo, especially in the Pacific market combined with our new freighter flying has led to a **strong** performance in this area.

Alimentation Couche-Tard Inc., June 29, 2022

This is stated by the impact of the **labor shortage** and a need to improve employee retention and increase of marketing initiatives and other discretionary expenses...

…if we can get over time down that's as we faced in the industry face **staffing shortages** last year. We expect that to moderate—if labor trends continue.

We are pleased to report really a remarkable year…nonetheless the **pandemic**, a war in Europe, supply chain, **staffing challenges** and now inflation.

While **supply chain issues** have been a challenge in some items, our expanded supplier relationships and duplicate supply sourcing have enabled us to improve our in-stock positions versus prior quarters.

I also want to take a moment and comment on the broad impact of **inflation** hitting a 40-year record high this quarter…we are impacted by the **inflationary pressures** in labor and fuel…

Bombardier, August 6, 2020

Let me start this morning by recognizing at first how **difficult** the past quarter has been for all of us. I certainly did not expect my first quarter back to be so **challenging** with the **COVID-19 pandemic** affecting nearly every aspect of our operation, our end markets, and our financial performance.

We also took the difficult step of announcing a **significant workforce adjustment** as we needed to realign our production rate to the current **COVID impacted** market condition...

Restaurant Brands International Inc., May 3, 2022

As we've mentioned in the past few quarters and similar to what others across the industry have noted, we are seeing a significant increase in **commodity volatility**, leading to **elevated levels of inflation**.

As mentioned last quarter, given the fact that we generally take a pasture approach, **inflation** has increased both our revenues and expenses, which in turn results in dilution of our percentage margin. We will continue to manage through the volatility that's extended into this year.

And obviously in more recent months by the **volatility** that we're seeing across North America, for the consumer, the **inflationary** environment is certainly something that's top of mind.

Source: Seeking Alpha LLC.